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# Artificial neural networks for controlling wind–PV power systems: A review

Kerim Karabacak [a,*], Numan Cetin [b]

[a] Kutahya Technical Sciences Vocational School, Dumlupinar University, Kutahya, Turkey
[b] Institute of Solar Energy, Ege University, Izmir, Turkey

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ABSTRACT

Nowadays, renewable energy systems are taking place than the conventional energy systems. Especially, PV systems and wind energy conversion systems (WECS) are taking a big role in supplying world's energy necessity. Efficiency of such types of renewable energy systems is being tried to be improved by using different methods. Besides conventional methods, intelligent system designs are seem to be more useful to improve efficiency of renewable energy systems. However, artificial neural networks (ANN) have many usage areas in modeling, simulation and control of renewable energy systems. ANNs are easy to use and to implement renewable energy system designs. In this paper, artificial neural network applications of PV, WECS and hybrid renewable energy systems which consist of PV and WECS are presented. Usage of neural network structures in such types of systems have been motivated.



**Contents**



* Corresponding author. Tel.: +90 274 227 04 50; fax: +90 274 227 04 54.
*E-mail address:* kerimkarabacak@gmail.com (K. Karabacak).

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## 1. Introduction

Artificial neural network (ANN) applications on renewable power systems in this paper are explained in a few parts: photovoltaic power systems, wind power systems and hybrid power systems which consist of PV and wind power systems. For solar energy, studies go on especially on prediction of solar irradiance for specific areas. Another ANN application area on solar power systems is sizing applications. Researchers have tried to find better ways for optimal sizing of photovoltaic power systems and they have tried to optimize the installation costs of these types of systems. However, solar cell models have been developed for analyzing power characteristics of PV (photovoltaic) cell elements. ANNs have also been used for maximum power point tracking (MPPT) simulations and applications for PV power systems. MPPTs try to hold the power system on maximum power gained operating point by ANN structures.

ANN applications on wind energy conversion systems (WECS) are mostly dependent on controlling pitch angle of wind turbine. However, ANNs have used the propeller of wind turbine to turn to the right direction to gain maximum performance from wind energy. As PV power systems, WECS are also an application area for MPPT implementation. The prediction of wind speed and direction is another working area for ANN applications of wind turbines.

Hybrid power system applications of ANN are about switching operations of wind and PV subsystems according to the environmental conditions. In most of the studies, ANN tries to decide which power generation subsystem will work on real time. MPPT applications of hybrid power systems are other focus points of ANN applications. Depending on the environmental changes (solar irradiance, humidity, temperature, wind) working percentage of solar power and wind power generation should be changed. ANN controllers decide these power generation percentages for each renewable energy module connected to the whole system.

## 2. Artificial neural networks

The ultimate goal of control engineering is to implement an automatic system which could operate with increasing independence from human actions in an unstructured and uncertain environment [1]. Such a system may be named as an autonomous or intelligent one. It would need only to be presented with a goal and would achieve its objective by continuous interaction with its environment through feedback about its behavior. It would continue to adapt and perform tasks with increasing efficiency under changing and unpredictable conditions. It would also be very useful when direct human interaction could be hazardous, prone to failures, or impossible [2].

Biological systems are a possible framework for the design of such an autonomous system. They provide several clues for the development of robust (highly stable) learning and adaptation algorithms required for this kind of systems. Biological systems process information differently than conventional control schemes; they are model free and are quite successful in dealing with uncertainty and complexity. They do not require the development of a mathematical model to execute complex tasks. Indeed, they can learn to perform new tasks and easily adapt to changing environments. If the fundamental principles of computation imbedded in the nervous systems are understood, an entirely new generation of control methods could be developed far beyond the capabilities of the present techniques based on explicit mathematical model. These new methods could serve to implement the ultimate intelligent systems [2].

### 2.1. Biological neural networks

Neurons, or nerve cells, are the building blocks of the nervous system. Although they have the same general organization and biochemical apparatus of other cells, they possess unique features. They have a distinctive shape, an outer membrane capable of generating electric impulses, and a unique structure: the synapse to transfer information from one neuron to other neurons. It is possible to distinguish three regions on this specialized cell [2]:

- the cell body,
- the dendrites,
- and the axon.

The cell body, or soma, provides the support functions and structure of the cell; it collects and processes information received from other neurons. The axon extends away from the cell body and provides the path over which information travel to other neurons. The dendrites are tube like extensions that branch repeatedly and form a bushy tree around the cell body; they provide the main path on which the neuron receives the coming information. A nerve impulse is triggered, at the origin of the axon, by the cell body in response to the received information; the impulse sweeps along the axon until it reaches the end. The junction point of an axon with a dendrite of another neuron is called a synapse, which consists of two parts: the knob like axon terminal and the receptor region. There, information is conveyed from neuron to neuron by means of chemical transmitters, which are released by arriving nerve impulses. Fig. 1 shows a scheme of the main neuron components [2].

The massive interconnection of neurons constitutes a biological neural network as presented in Fig. 2.

Looking at the neuron in more detail, we can think of it as a tiny battery. In fact, neurons are filled and surrounded by fluids which contain dissolved chemicals; the fluid inside is a big contrast to the one outside. Inside and around the cell body or soma are calcium ($Ca^{++}$), chloride ($CL^{-}$), potassium ($K^{+}$) and sodium ($Na^{+}$). $K^{+}$ ions are concentrated inside the neuron and $Na^{+}$ ones outside

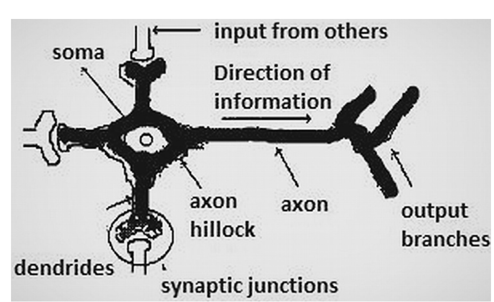


**Fig. 1.** Biological neuron model [2].

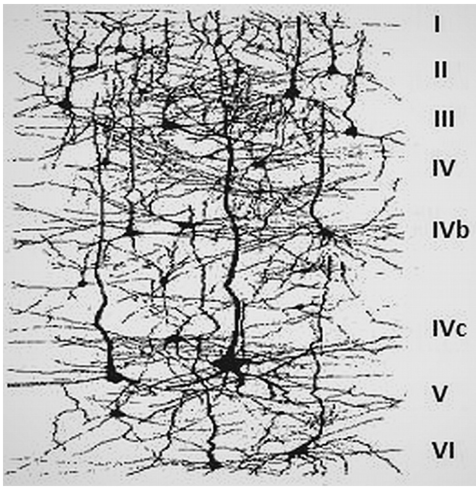


**Fig. 2.** A biological neural network with layers [2].

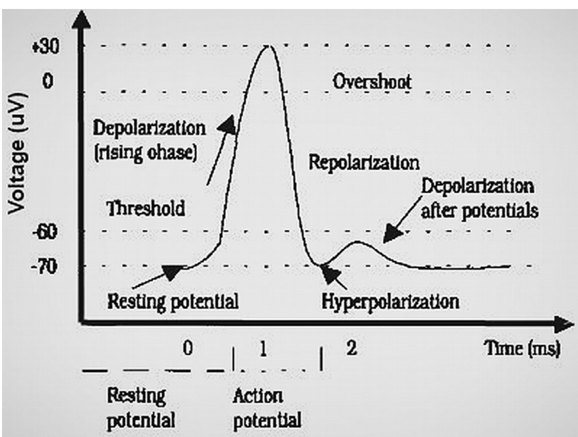


**Fig. 3.** Generation of nerve impulse [2].

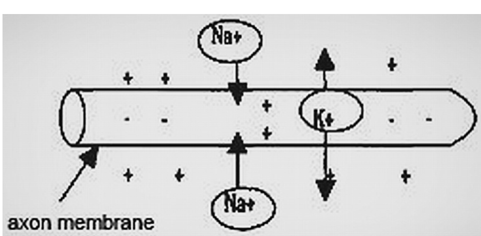


**Fig. 4.** Nerve impulse [2].

of it; these ions are responsible for generating the nerve pulse. In an unexcited state there is only a minimal ion current through the membrane, and the voltage inside with neural networks structures 7 in respect to the outside (membrane potential) rests constant at about −70 mV. If the cell body is stimulated by a voltage greater than a certain threshold, a current of ions is established: Na+ into the cell body and K+ out of it, changing the cell body internal state by the increasing of the membrane potential. A scheme of synapse is shown in Fig. 3. In terms of information processing the synapse performs a nerve impulse train frequency to voltage conversion [2].

Fig. 4 shows the progression of nerve impulse along axon.

### 2.2. Neuron model

An artificial neural network (ANN) is a massively parallel distributed processor inspired from biological neural networks, which can store experimental knowledge and make it available for use [3]. It has some similarities with the brain, such as

1. Knowledge is acquired through a learning process.
2. Interneuron connectivity named as synaptic weights is used to store this knowledge.

The procedure for the learning process is known as a learning algorithm. Its function is to modify the synaptic weights of the networks in order to attain a prespecified goal. The weight modification provides the traditional method for neural networks design and implementation. The neuron is the fundamental unit for the operation of a neural network. Fig. 5 presents a neuron scheme. There are three basic elements:

1. A set of synapsis links, with each element characterized by its own weight.
2. An adder for summing the inputs signal components, multiplied by the respective synapsis weight.
3. A nonlinear activation function transforming the adder output into the output of the neuron.

Fig. 6, which is characterized by

- Input nodes, which supply the input signal to the neuron.
- The neuron is represented by a single node, named as a computation one.
- Communication links interconnecting the input nodes and the computation ones.

### 2.3. Neural networks structures

The way in which the neurons of a neural network are interconnected determines its structure. For the purposes of identification and control, the most used structures are as follows:

1. Single-layer feedforward networks.
2. Multilayer feedforward networks.

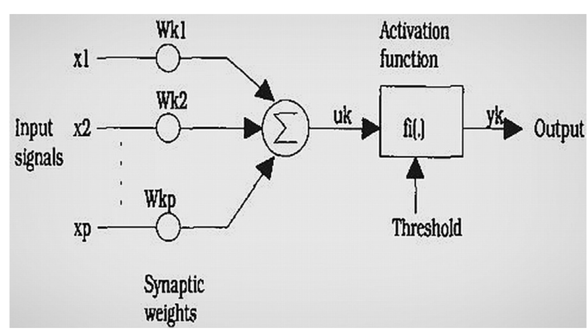


**Fig. 5.** Nonlinear model of a neuron [2].

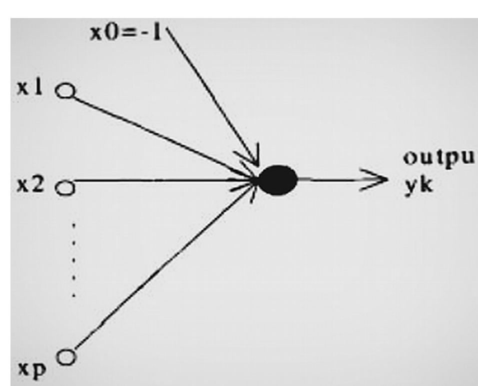


**Fig. 6.** Simplified scheme of a neuron [2].

3. Radial basis networks.
4. Dynamic (differential) or recurrent neural networks.

### 2.3.1. Single-layer feedforward networks

It is the simplest form of feedforward networks. It has just one layer of neurons as shown in Fig. 7. The best known is the so called perceptron. Basically it consists of a single neuron with adjustable synaptic weights and threshold [2].

### 2.3.2. Multilayer feedforward neural networks

They distinguish themselves by the presence of one or more hidden layers (Fig. 8) whose computation nodes are called hidden neurons. Typically the neurons in each layer have the output signals of the preceding layer as their inputs. If each neuron in each layer is connected to every neuron in the adjacent forward layer, then the neural network is named as fully connected, on the opposite case, it is called partly connected [2].

### 2.3.3. Radial basis function neural networks

Radial basis function (RBF) neural networks have three entirely different (Fig. 9).

1. The input layer made up of input nodes.
2. The hidden layer, with a high enough number of nodes (neurons). Each of these nodes performs a nonlinear transformation of the input, by means of radial basis functions.
3. The output layer, which is a linear combination of the hidden inputs neurons. Radial basis functions were first introduced for the solution of multivariate interpolation problems; early works on this approach are surveyed in [4]. The first application of radial basis functions to neural networks design is reported in [5].

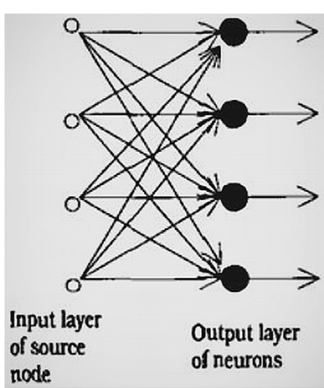


**Fig. 7.** Single-layer feedforward network [2].

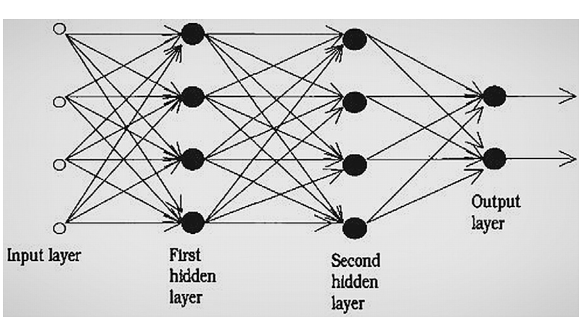


**Fig. 8.** Multilayer feedforward network [2].

### 2.3.4. Recurrent neural networks

A common approach for encoding temporal information using static neural networks is to include delaying inputs and outputs. However, this representation is limited, since it can only encode a finite number of the previous measured outputs and imposed inputs; moreover, it tends to require prohibitively large amounts of memory, thereby hindering its use for all but relatively low order dynamical systems. As a very efficient and promising alternative, the international research community has been exploring the use of recurrent or dynamic neural networks [2] (Fig. 10).

Recurrent or dynamic neural networks distinguish themselves from static neural networks in which they have at least one feedback loop. One of the first surveys of structures, learning algorithms and applications of this kind of neural networks is given in [6]. There, it is signaled that neural networks, whose structures include feedback, are present from the very earliest development of artificial neural networks; in fact, in [7], McCulloch and Pitts developed models for feedforward networks, which have time dependence and time delays; however, these networks were implemented with threshold logic neurons. Then, they extended their network to those with dynamic memory; these networks had feedback. Later, these networks were modeled as finite automata with a regular language in [8], which is usually referenced as the first work on this kind of automata.

## 2.4. Neural networks in control

In reference to neural networks in control, the following characteristics and properties are important [2]:

1. *Nonlinear systems*: neural networks offer a great promise in the realm of nonlinear control. This stems from their theoretical capability to approximate arbitrary nonlinear functions.

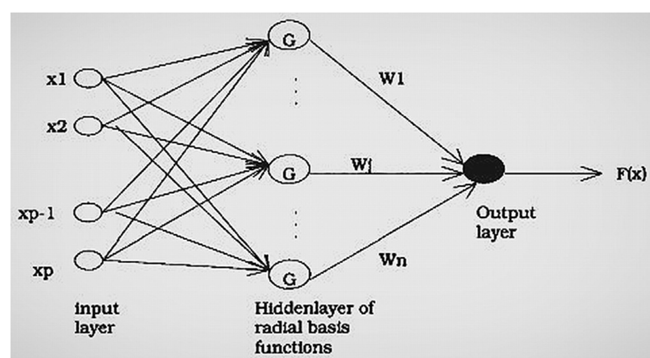


**Fig. 9.** Radial basis function network [2].

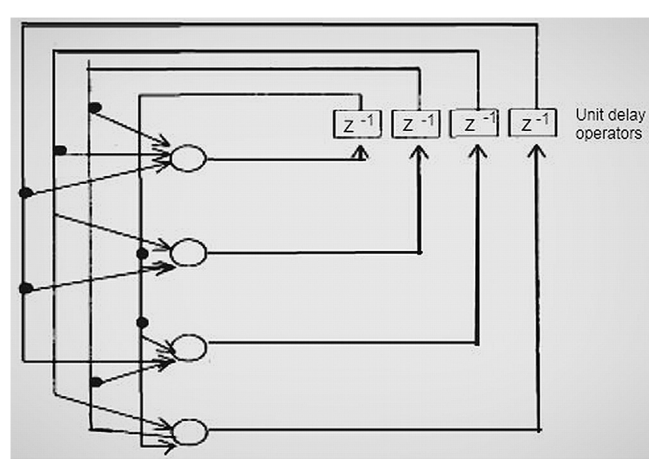


**Fig. 10.** Discrete time recurrent neural networks [1].

2. *Parallel distributed processing*: neural networks have a highly parallel structure, which allows parallel implementations immediately.
3. *Learning and adaptation*: neural networks are trained by using data from the system under study. An adequately trained neural network has the ability to generalize for the inputs not appearing in the training data. Moreover, they can also be adapted on-line.
4. *Multivariate systems*: neural networks have the ability to process many inputs and outputs; they are readily applicable to multivariable systems.

## 3. ANN usage of wind, PV or hybrid power systems

In recent days, artificial intelligence techniques are rising for the optimization and control of renewable power systems instead of conventional control and optimization methods. They are improving efficiency of renewable power generation.

In the literature, multiobjective functions and risk constrained analyses take important position. Nayeripour et al. [9] proposed a new Pareto-based multi-objective problem for the placement and sizing of multiple micro-turbines in a distribution network to improve the transient stability index in addition to the losses and voltage profile. To calculate the transient stability index, the rates of fault occurrence in the different locations are considered. Also, the loads are modeled as both constant power and voltage dependent cases. In order to identify Pareto optimal solutions of the optimization problem, a novel hybrid evolutionary algorithm based on the Particle Swarm Optimization (PSO) and Shuffled Frog-Leaping (SFL) algorithm is presented.

Aghaei et al. [10] investigated demand responses in smart electricity equipped with renewable energy sources. Successful demand response implementations around the world are analyzed.

Gitizadeh et al. [11] introduced a new multiobjective framework for GEP problem. The proposed MOGEP model, owning MILP formulation, includes cost function, emission and risk of fuel prices as the competing objective functions. Furthermore, the results show the trade-off between the presented objectives. Therefore, the decision maker is able to choose the best combination of the plants upon its needs. To cope with the MOGEP problem, a new multiobjective framework named MNBI, composed of lexicographic optimization (for the calculation of a more effective payoff table) and NMI method, has been proposed.

Ghadikolaei et al. [12] considered a practical methodology of risk measurement and management model for hybrid wind/hydro generation scheduling that allows GENCO to manage the risk of wind generation and market price uncertainties in the day-ahead energy/reserve market. The proposed risk constrained market model is based on the optimization procedure for the maximization of the expected profits in the presence of risk constraints considering novel weighted risk coefficients as maximum expected downside risk. The risks associated with the stochastic resources and uncertain market price are weighted in the different sub-cases under various amounts of allowable risk tolerance and the proposed risk constrained WHPS model is investigated for each case. The reported results demonstrate that the expected net profits and profit loss due to the risk constraint would be different depending on the important coefficient of the considered uncertain parameters. As can be seen in the present work, when importance weight of wind generation uncertainty increases during WHPS risk management model, GENCO might confront with unexpected profit tolerance which has to be exactly investigated by GENCO's owner in practical cases. With the application of the proposed risk constrained WHPS market model, GENCO is able to adopt different risk-control bidding strategies to gain acceptable benefit/risk trade-off between the expected benefits of financial activities and how much risk it is willing to assume.

Aghaei et al. [13] presented a multiperiod multiobjective generation expansion planning (MMGEP) model of power electric system including renewable energy sources (RES). The model optimizes simultaneously multiple objectives (i.e. minimization of total costs, emissions, energy consumption and portfolio investment risk as well as maximization of system reliability). The mixed-integer linear programming (MILP) is used for the proposed optimization and an efficient linearization technique is proposed to convert the nonlinear reliability metrics into a set of linear expressions. The proposed solution for multiobjective mathematical programming (MMP) framework includes a hybrid augmented–weighted epsilon constraint and lexicographic optimization approach to obtain the Pareto optimal or efficient solutions for the MMGEP problem. Finally, fuzzy decision making is implemented to select the most preferred solution among Pareto solutions based on the goals of decision makers (DMs). A synthetic test system including seven types of candidate units is considered here for GEP in a 6-year planning horizon. The effectiveness of the proposed modifications is illustrated in detail.

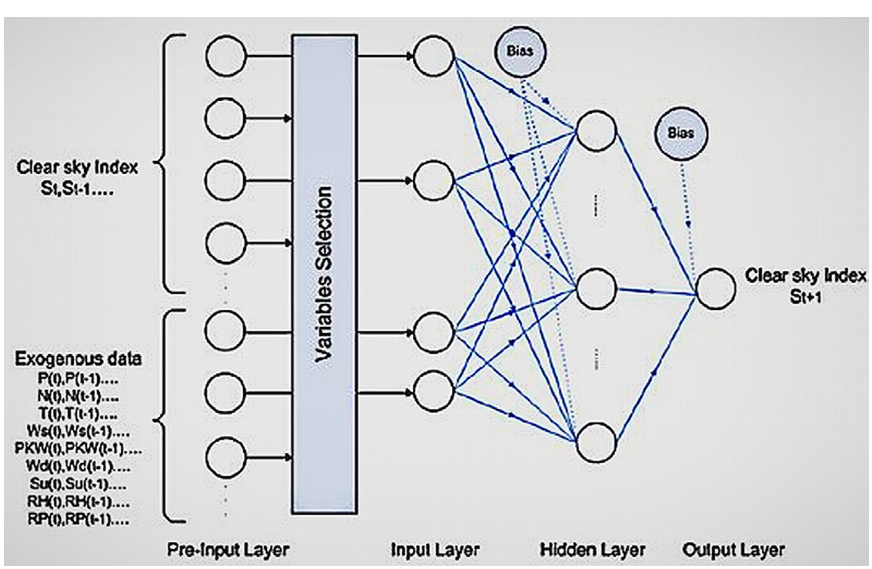


**Fig. 11.** Detail of the overall real system prediction [16].

Supporting the optimization techniques above, artificial neural networks have lots of application areas in modeling, simulation and control of renewable energy systems. In this paper, its application areas are classified as PV, wind and hybrid power systems.

### 3.1. PV power systems

ANN applications of PV systems are mostly based on prediction of solar irradiance and sizing of PV systems. However, there are several applications and simulations on modeling of solar cells, design of maximum power point tracking (MPPT) and active demand controller designs.

#### 3.1.1. Prediction of solar irradiance by ANN

ANN structures have the capability of predicting future system output values according to old input and output values. However, solar irradiance is very important for solar energy systems. Power generation of solar energy systems is proportional with the intensity of solar irradiance. So, ANN structures have been used in many applications for predicting solar irradiance. Chen et al. [14] have developed a simplified approach for forecasting 24-h ahead of power generation using a radial basis function network (RBFN). Almonacid et al. [15] applied an ANN structure for estimating solar energy from PV panels on a car park and different buildings. Voyant et al. [16] designed an optimum ANN for multi-variate forecasting of daily global radiation. Detailed system design for predicting solar irradiance is given in Fig. 11.

Mellit et al. [17] have also designed an ANN for 24 h forecast of solar irradiance. A multilayer feedforward network structure has been used for that study. Fig. 12 shows measured and forecasted solar irradiance.

Paoli et al. used a multilayer perceptron and an ad hoc time series pre-processing to develop a methodology for the daily prediction of global solar radiation on a horizontal surface [18]. Table 1 shows the comparison of ANN and the other prediction methods.

Mellit et al. presented a suitable adaptive neuro-fuzzy inference system (ANFIS) model for estimating sequences of mean monthly clearness index (View the Math ML source $\bar{K}t$) and total solar radiation data in isolated sites based on geographical coordinates. The magnitude of solar radiation is the most important parameter

**Table 1**
Evaluation of the prediction quality for all prediction methods, forecasting years 1988 and 1989, 1 day horizon [18].

| Prediction method | nRMSE (%) ± 95% IC | RMSE ($MJ/m^2$) | MAE ($MJ/m^2$) | $R^2$ | MBE ($MJ/m^2$) |
|---|---|---|---|---|---|
| Naïve predictor (persistence) | 26.13 ± 0.00 | 4.65 | 3.03 | 0.69 | −0.001 |
| Naïve predicto r (daily average) | 22.52 ± 0.00 | 4.01 | 3.11 | 0.75 | −0.39 |
| Markov Chain (order 3) | 25.85 ± 0.00 | 4.59 | 3.03 | 0.69 | −0.23 |
| Bayes (order 3) | 25.57 ± 0.00 | 4.55 | 3.01 | 0.69 | −0.13 |
| *k*-NN (order 10) | 25.20 ± 0.00 | 4.48 | 3.19 | 0.70 | −0.03 |
| AR(8) | 21.18 ± 0.00 | 3.77 | 2.85 | 0.78 | −0.61 |
| ANN [8,3,1] | 20.97 ± 0.15 | 3.73 | 2.82 | 0.79 | −0.58 |

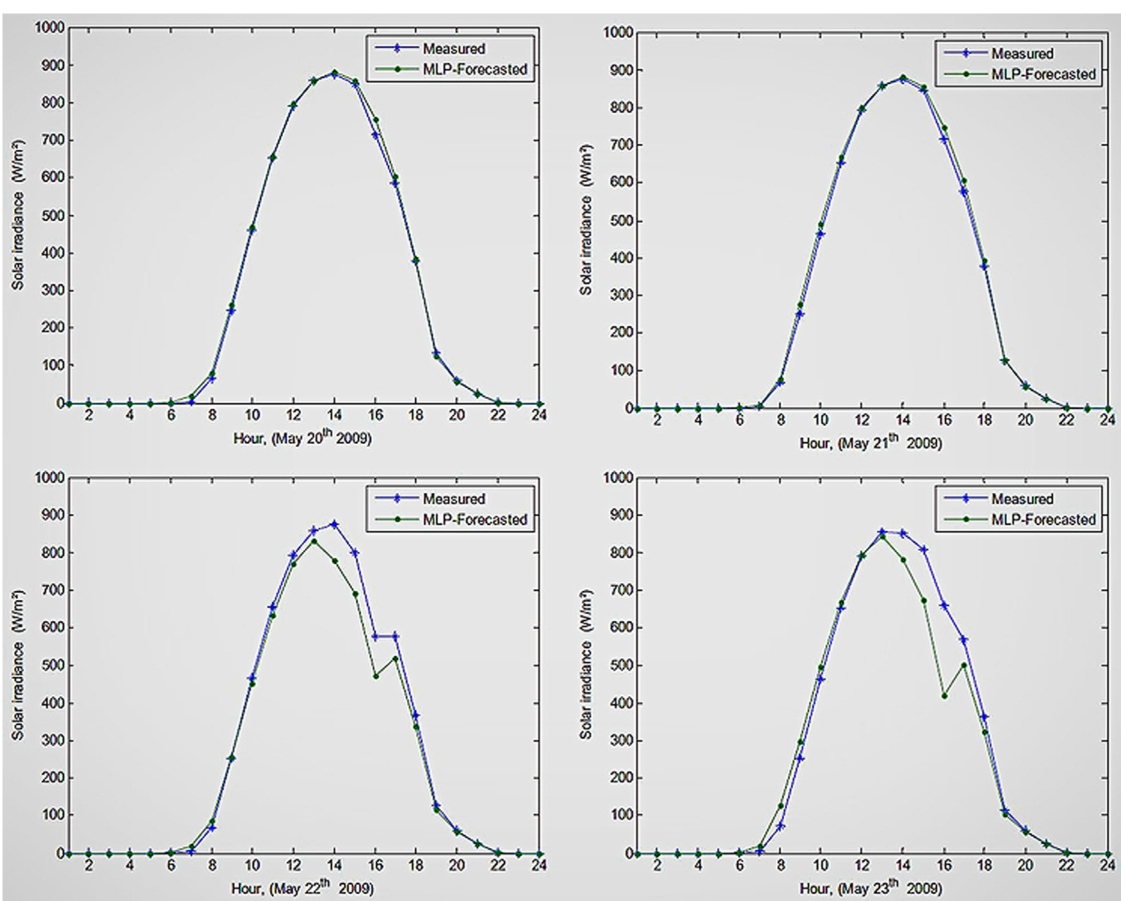


**Fig. 12.** Comparison between measured and forecasted solar irradiance values 24 h ahead at Trieste in Italy during period May 20–23 2009 (sunny days) [17].

for sizing photovoltaic (PV) systems. The ANFIS model is trained by using a multilayer perceptron (MLP) based on fuzzy logic (FL) rules. The inputs of the ANFIS are the latitude, longitude, and altitude, while the outputs are the 12-values of mean monthly clearness index View the Math ML source $\bar{K}t$. These data have been collected from 60 locations in Algeria. The results show that the performance of the proposed approach in the prediction of mean monthly clearness index View the Math ML source $\bar{K}t$ is favorably compared to the measured values. The root mean square error (RMSE) between measured and estimated values varies between 0.0215 and 0.0235 and the mean absolute percentage error (MAPE) is less than 2.2% [19].

In another study of Mellit et al., an artificial neural network is used for modeling and predicting the power produced by a 20 kWp GCPV plant installed on the roof top of the municipality of Trieste (latitude 45°40′N, longitude 13°46′E), Italy. An experimental database of climate (irradiance and air temperature) and electrical (power delivered to the grid) data from January 29 to May 25 2009 has been used. Two ANN models have been developed and implemented on experimental climate and electrical data. The first one is a multivariate model based on the solar irradiance and the air temperature, while the second one is an univariate model which uses as input parameter only the solar irradiance. A database of 3437 patterns has been divided into two sets: the first (2989 patterns) is used for training the different ANN models, while the second (459 patterns) is used for testing and validating the proposed ANN models. Prediction performance measures such as correlation coefficient (*r*) and mean bias error (MBE) are presented. The results show that good effectiveness is obtained between the measured and the predicted power produced by the 20 kWp GCPV plant. In fact, they found correlation coefficient is in the range 98–99%, while the mean bias error varies between 3.1% and 5.4% [20].

Benghanem et al. used a radial basis function (RBF) network for modeling and predicting the daily global solar radiation data using other meteorological data such as air temperature, sunshine duration, and relative humidity. These data were recorded in the period 1998–2002 at Al-Madinah (Saudi Arabia) by the National Renewable Energy Laboratory. Four RBF-models have been developed for predicting the daily global solar radiation. It was found that the RBF-model which uses the sunshine duration and air temperature as input parameters gives accurate results as the correlation coefficient in this case is 98.80% [21].

Wang et al. presented a novel ANN-based solar irradiance forecasting model using statistical feature parameters of irradiance and ambient temperature. Based on the description of solar irradiance variation, the relationship between surface irradiance and extraterrestrial irradiance is figured out. The input vector is reconstructed and it is composed of only five components. Thus the input dimension is reduced effectively without data information loss. Simulation and discussion are carried out to validate the proposed model. The analysis of the different working mechanisms of the novel model and the other models was also discussed. The comparison of measured data with forecasted values shows that the proposed model is both reliable and more effective. Furthermore, the simulation results also illustrated that the forecast accuracy is greatly improved by the new model under changeable weather conditions [22].

Fernandez-Jimenez et al. presented a new statistical short-term forecasting system for a grid connected photovoltaic (PV) plant. The proposed system comprises three modules composed of two numerical weather prediction models and an artificial neural network-based model. The first two modules are used to forecast weather variables used by the third module, which has been selected from a set of different models. The final forecast value is the hourly energy production in the PV plant. The forecasting horizon ranges from 1 to 39 h, covering all the following days [23].

Mellit et al. developed a hybrid model which will be used to predict the daily global solar radiation data by combining an artificial neural network (ANN) and a library of Markov transition matrices (MTM) approach. Developed model can generate a sequence of global solar radiation data using a minimum of input data (latitude, longitude and altitude), especially in isolated sites. A database of daily global solar radiation data has been collected from 60 meteorological stations in Algeria during 1991–2000. Also a typical meteorological year (TMY) has been built from this database. Firstly, a neural network block has been trained based on 60 known monthly solar radiation data from the TMY. In this way, the network was trained to accept and even handle a number of unusual cases. The neural network can generate the monthly solar radiation data. Secondly, these data have been divided by the corresponding extraterrestrial value in order to obtain the monthly clearness index values. Based on these monthly clearness indexes and using a library of MTM block we can generate the sequences of daily clearness indexes. Known data were subsequently used to investigate the accuracy of the prediction. Furthermore, the unknown validation data set produced very accurate prediction, with an RMSE error not exceeding 8% between the measured and the predicted data. A correlation coefficient ranging from 90% and 92% has been obtained; also this model has been compared to the traditional models AR, ARMA, Markov chain, MTM and measured data. The results obtained indicate that the proposed model can successfully be used for the estimation of the daily solar radiation data for any locations in Algeria by using as inputs the altitude, the longitude, and the latitude. Also, the model can be generalized for any location in the world. An application of sizing PV systems in isolated sites has been applied in order to confirm the validity of this model [24].

Maqsood et al. present a comparative study of different neural network models for forecasting the weather of Vancouver, British Columbia, Canada. For developing the models, one year's data are used comprising daily maximum and minimum temperature and wind speed. A multi-layered perceptron (MLP) and an Elman recurrent neural network (ERNN) were trained using the one-step-secant and Levenberg–Marquardt algorithms. To ensure the effectiveness of neurocomputing techniques, we also tested the different connectionist models using a different mining and test data set. Experimental results obtained have shown radial basis function network (RBFN) that produced the most accurate forecast model compared to ERNN and MLP [25].

In another study, Maqsood et al. investigated the development of a reliable and efficient neurocomputing technique to forecast the peak weather in Vancouver, British Columbia, Canada. For developing the models, one year's data comprising daily maximum temperature, wind speed and visibility are used. Experiment results demonstrate that neuro-forecast models show a very good prediction performance and the approach is effective and reliable [26].

Maqsood et al. examined the applicability of Hopfield Model (HFM) for weather forecasting in southern Saskatchewan, Canada. The model performance is contrasted with multi-layered perceptron network (MLPN), Elman recurrent neural network (ERNN) and radial basis function network (RBFN). The data of temperature, wind speed and relative humidity were used to train and test the four models. With each model, 24-h ahead forecasts were made for winter, spring, summer and fall seasons. Moreover, ensembles of these models were generated by choosing the best values among the four predicted outputs that were closest to the actual values. Performance and reliabilities of the models were then evaluated by a number of statistical measures. The results indicate that the HFM was relatively less accurate for the weather forecasting problem. In comparison, the ensembles of neural networks and RBFN produced the most accurate forecasts [27].

Maqsood et al. presented a comparative analysis of different connectionist and statistical models for forecasting the weather of Vancouver, Canada. For developing the models, one year's data

comprising daily temperature and wind speed were used. A multi-layered perceptron network (MLPN) and an Elman recurrent neural network (ERNN) were trained using the one-step-secant and Levenberg–Marquardt algorithm. Radial basis function network (RBFN) was employed as an alternative to examine its applicability for weather forecasting. To ensure the effectiveness of neurocomputing techniques, the connectionist models were trained and tested using different datasets. Moreover, ensembles of the neural networks were generated by combining the MLPN, ERNN and RBFN using arithmetic mean and weighted average methods. Subsequently, the performance of the connectionist models and their ensembles was compared with a well-established statistical technique. Experimental results obtained have shown that RBFN produced the most accurate forecast model compared to ERNN and MLPN. Overall, the proposed ensemble approach produced the most accurate forecast, while the statistical model was relatively less accurate for the weather forecasting problem considered [28].

Maqsood et al. examined regularized forward selection (RFS) – a combination of forward subset selection and zero-order regularization. An efficient implementation of RFS into which either delete-1 or generalized cross-validation can be incorporated and a re-estimation formula for the regularization parameter are also discussed. Simulations that demonstrate improved generalization performance due to the regularization in the forward selection of radial basis function centers [29] are presented.

Table 2 shows a list of ANN usage for the prediction of solar irradiance according to ascending years.

#### 3.1.2. Modeling and simulation of PV systems

The prediction of PV module behaviors under natural sunlight can be made by numerical or algebraic methods. Caamaño et al. provided a method which consists of technical and contractual procedures, both closely related [30]. Wagner et al. used an approach with the distribution of solar irradiance by a mathematical method [31]. A guideline is prepared for the assessment of photovoltaic plants by Blaaser et al. [32]. In another study, solar cell theory is discussed [33]. Translation of photovoltaic performance measurements is discussed in another study [34]. Procedure for temperature and irradiance corrections to measure *V–I* characteristics of crystalline silicon photovoltaic devices is given by classical methods [35]. Guidelines of assessments of photovoltaic plants are also determined in Ref. [36]. In Refs. [37,38], a linear interpolation method is used for current–voltage curve translation. PVUSA photovoltaic systems are discussed in Ref. [39]. Field experiences of numerical and algebraic methods are presented in Ref. [40]. However, artificial neural networks are an alternative method for modeling such PV module parameters and characterization.

Balzani and Reatti [41] presented an application of ANN for modeling a PV module. A feedforward neural network consisting of two hidden layers was used in this simulation. The results of this work are useful to estimate the site productivity and to proceed to a correct design and optimization of the entire PV system. The mean values of the errors between actual and predicted values are presented in Table 3.

Mellit et al. [42] used two types of ANN: the MLP and the RBF for modeling and simulation of the electrical signals from an SAPV. Fig. 13 shows the RBF network with IIR filter for estimating the electrical signal of an SAPV. Authors also used RBF network for predicting signals from the monitoring of stand-alone PV systems [43].

In addition, an adaptive ANN has been used for the modeling and simulation of an experimental PV system [44]. For each component of

**Table 3**
Error between the actual and the predicted values [41].

| Test set | Absolute error | |
|---|---|---|
| | Voltage | Current |
| Test set 1 | 0.2517 | 0.0509 |
| Test set 2 | 0.3022 | 0.0625 |
| Test set 3 | 0.3589 | 0.0357 |

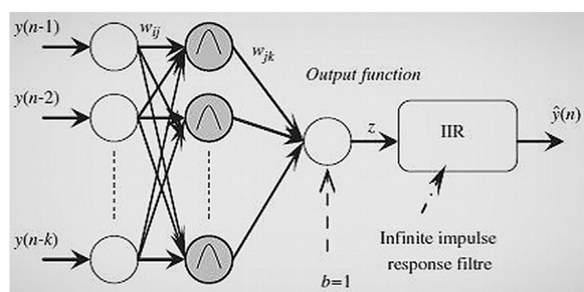


**Fig. 13.** RBF-IIR model for generating the signals from PV system [43].

**Table 2**
List of ANN usage for the prediction of solar irradiance.

| No. | Subject | Year | Ref. no. |
|---|---|---|---|
| 1 | Canadian weather analysis using connectionist learning paradigms | 2002 | [25] |
| 2 | Neurocomputing based Canadian weather analysis | 2002 | [26] |
| 3 | Intelligent weather monitoring systems using connectionist models | 2002 | [27] |
| 4 | A simplified model for generating sequences of global solar radiation data for isolated sites: using artificial neural network and a library of Markov transition matrices approach | 2005 | [24] |
| 5 | Application of soft computing models to hourly weather analysis in southern Saskatchewan | 2005 | [29] |
| 6 | Methodology for predicting sequences of mean monthly clearness index and daily solar radiation data in remote areas: application for sizing a stand-alone PV system | 2007 | [19] |
| 7 | Weather analysis using ensemble of connectionist learning paradigms | 2007 | [28] |
| 8 | Estimation of the energy of a PV generator using artificial neural network | 2009 | [15] |
| 9 | Optimization of an artificial neural network dedicated to the multivariate forecasting of daily global radiation | 2010 | [16] |
| 10 | A 24-h forecast of solar irradiance using artificial neural network: application for performance prediction of a grid connected PV plant at Trieste, Italy | 2010 | [17] |
| 11 | Forecasting of preprocessed daily solar radiation time series using neural networks | 2010 | [18] |
| 12 | Performance prediction of 20 kWp grid connected photovoltaic plant at Trieste (Italy) using artificial neural network | 2010 | [20] |
| 13 | Radial basis function network-based prediction of global solar radiation data: application for sizing of a stand-alone photovoltaic system at Al-Madinah, Saudi Arabia | 2010 | [21] |
| 14 | On-line 24-h solar power forecasting based on weather type classification using artificial neural network | 2011 | [14] |
| 15 | Short-term solar irradiance forecasting model based on artificial neural network using statistical feature parameters | 2012 | [22] |
| 16 | Short-term power forecasting system for photovoltaic plants | 2012 | [23] |

the PV system, an ANN-model is developed (ANN-PV generator, ANN battery and ANN-regulator). Fig. 35 shows the different ANN models used for the modeling and simulation of PV system. The MRE between the experimental and the ANN results estimated by the model is between 2.5% and 8.5%. Authors used an ANN that combines the Levenberg–Marquardt algorithm (LM) with an infinite impulse response (IIR) filter in order to accelerate the convergence of the network in another study [45]. An adaptive artificial neural network for the modeling and simulation of a stand-alone photovoltaic power system [46] and artificial intelligence-based modeling and simulation of a stand-alone photovoltaic power supply system are also given by Mellit et al. [47].

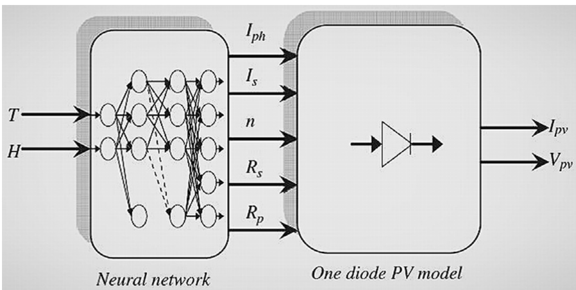


**Fig. 14.** The basic configuration of the proposed PV model [48].

**Table 4**
The MSE and the regression analysis between *V–I* curves measured at different outdoor conditions and those obtained by the MLP in the training process, for modules in the study [51].

| $G$ (W/m$^2$) | $T_c$ (°C) | MSE (%) | Best linear fit: $A=mT+b$ | $R$-value |
|---|---|---|---|---|
| *ISOFOTON I-106* | | | | |
| 200.37 | 41.04 | 6.67 | $A=(0.9974)T+(0.0146)$ | 1.0000 |
| 226.50 | 18.47 | 0.05 | $A=(0.9990)T+(0.0090)$ | 1.0000 |
| 600.08 | 54.80 | 3.90 | $A=(0.9971)T+(0.0349)$ | 1.0000 |
| 700.50 | 22.71 | 0.04 | $A=(1.0027)T+(-0.0426)$ | 1.0000 |
| 801.31 | 50.77 | 0.04 | $A=(0.9966)T+(0.0020)$ | 1.0000 |
| 841.37 | 24.25 | 0.27 | $A=(1.0091)T+(-0.0655)$ | 0.9998 |
| 1000.35 | 57.62 | 4.20 | $A=(1.0054)T+(-0.0419)$ | 0.9998 |
| 1087.44 | 30.21 | 0.02 | $A=(1.0075)T+(-0.0363)$ | 1.0000 |
| 1227.71 | 26.29 | 0.27 | $A=(0.9808)T+(0.1665)$ | 0.9997 |
| 1284.89 | 47.04 | 0.06 | $A=(1.0000)T+(-0.0200)$ | 0.9999 |
| *Shell RMS 100S* | | | | |
| 236.47 | 18.81 | 1.34 | $A=(0.9994)T+(-0.0029)$ | 1.0000 |
| 252.73 | 38.81 | 1.33 | $A=(0.9995)T+(0.0161)$ | 1.0000 |
| 606.50 | 42.10 | 1.22 | $A=(1.0002)T+(0.0023)$ | 1.0000 |
| 695.82 | 24.16 | 0.78 | $A=(1.0036)T+(-0.0242)$ | 1.0000 |
| 818.75 | 55.04 | 0.67 | $A=(0.9991)T+(-0.0794)$ | 1.0000 |
| 819.08 | 33.08 | 0.14 | $A=(0.9999)T+(0.0594)$ | 1.0000 |
| 1007.68 | 31.32 | 0.33 | $A=(0.9940)T+(0.0638)$ | 0.9999 |
| 1024.28 | 56.46 | 1.61 | $A=(1.0011)T+(-0.0962)$ | 0.9999 |
| 1100.83 | 62.05 | 0.03 | $A=(0.9990)T+(0.0500)$ | 1.0000 |
| 1213.09 | 27.69 | 0.035 | $A=(1.0018)T+(0.0266)$ | 1.0000 |

Karatepe et al. [48] used a neural network-based approach for improving the accuracy of the electrical equivalent circuit of a PV module. The equivalent circuit parameters of a PV module mainly depend on solar irradiation and temperature. The dependence on environmental factors on the circuit parameters is investigated by using a set of current–voltage curves. It is shown that the relationship between them is nonlinear and cannot be easily expressed by any analytical equation. Fig. 14 presents the basic configuration of the proposed PV model. The comparison between the measured values and the proposed model results shows higher accuracy than the conventional model for all operating conditions.

Ohsawa et al. [49] applied an ANN for the operation and control of PV–diesel systems. El-Tamaly and Elbaset [50] presented a complete study from the reliability point of view to determine the impact of interconnecting PV/wind energy system (WES) hybrid electric power system (HEPS) into utility grid (UG). Four different configurations of PV/WES/UG have been investigated and a comparative study between these four different configurations has been carried out. The overall system is divided into three subsystems, containing the UG, PV and WES. The generation capacity outage table has been built for each configuration of these subsystems. The capacity outage tables of UG, PV/UG, WES/UG and PV/WES/UG are calculated and updated to incorporate their fluctuating energy production. A FL technique is used to calculate and assess the reliability of the system.

Almonacid et al. characterized Si-crystalline PV modules by artificial neural networks [51]. An ANN has been developed which is able to generate *V–I* curves of Si-crystalline PV modules for any irradiance and module cell temperature. The results show that the proposed ANN introduces a good accurate prediction for Si-crystalline PV modules' performance when compared with the measured values. Table 4 shows the MSE (mean square error) and the regression analysis between *V–I* curves measured at different outdoor conditions and those obtained by the MLP in the training process, for modules in the study. In the table, its shown that the MSE is smaller than 6.67% and an average MSE is approximately about 1.55%.

There are several other works that model and simulate PV power systems. Moh'd Sami et al. modeled a photovoltaic solar integrated system with artificial neural networks [52]. Almonacid et al. compared the characterization of PV CIS module by artificial neural networks with other methods [53]. Bonanno et al. used a radial basis function neural network-based approach for the electrical characteristics estimation of a photovoltaic module [54]. Table 5 shows a summary of studies on the modeling and simulation of PV systems.

**Table 5**
List of ANN usage for modeling and simulation of PV systems.

| No. | Subject | Year | Ref. no. |
|---|---|---|---|
| 1 | Optimal operation of photovoltaic/diesel power generation system by neural network | 1993 | [49] |
| 2 | Prediction and modeling signals from the monitoring of stand-alone PV systems using an adaptive neural network model | 2004 | [42] |
| 3 | An adaptive radial basis function network model for the prediction signals from the monitoring of stand-alone PV systems | 2004 | [43] |
| 4 | Neural network-based model of a PV array for the optimum performance of PV system | 2005 | [41] |
| 5 | Modeling and simulation of stand-alone photovoltaic power system using artificial neural network | 2005 | [44] |
| 6 | An adaptive artificial neural network for modeling and simulation of a stand-alone photovoltaic power system | 2005 | [46] |
| 7 | Artificial intelligence-based modeling and simulation of a stand-alone photovoltaic power supply system | 2006 | [47] |
| 8 | Neural network-based solar cell model | 2006 | [48] |
| 9 | Impact of interconnection photovoltaic/wind system with utility on their reliability using a fuzzy scheme | 2006 | [50] |
| 10 | Modeling and simulation of a stand-alone photovoltaic system using an adaptive artificial neural network | 2007 | [45] |
| 11 | Optimization and modeling of a photovoltaic solar integrated system by neural networks | 2008 | [52] |
| 12 | Characterization of Si-crystalline PV modules by artificial neural networks | 2009 | [51] |
| 13 | Characterization of PV CIS module by artificial neural networks | 2010 | [53] |
| 14 | A radial basis function neural network-based approach for the electrical characteristics estimation of a photovoltaic module | 2012 | [54] |

### 3.1.3. Maximum power point tracking

Another usage area of neural networks in renewable power systems is the maximum power point tracking of PV modules. Veerachary and Yadaiah [55] proposed the application of an ANN for the identification of the optimal operating point of a PV supplied separately to the excited dc motor driving two different load torques. A gradient descent algorithm is used to train the ANN controller for the identification of the maximum power point of the solar cell array (SCA) and the gross mechanical energy operation of the combined system. The adaptive controller using ANN is tested for different sets of solar insolation and the results are close to the computed values. The developed controller can also be extended for the PV supplied PM and series motors. According to the authors, the ANN provides a highly accurate identification/tracking of optimal operating points even with stochastically varying solar insolation [56].

Hiyama and Kitabayashi [57] used a neural network for estimating the maximum power generation from PV module using environmental information. The proposed network can be utilized for the prediction of the next day's generation from the PV systems by using the predicted information from the weather offices. According to the authors, the proposed method gives more accurate prediction compared to the prediction obtained by using the conventional multiple regression models [56].

A new robust control method and its application to a PV supplied to a separately excited dc motor loaded with a constant torque are discussed in Ref. [58]. The robust controller is designed against the load torque changes by using the first and the second ordered derivatives of the universal learning networks (ULNs). The simulation results showed that the robustness of the control system is improved although the motor load torque at the control stage is different from that at the training stage [56].

Theodore et al. [59] used an ANN MPPT for solar electric vehicles. The MPPT is based on a highly efficient boost converter with insulated gate bipolar transistor (IGBT) power switch. The reference voltage for the MPPT is obtained by an ANN with gradient descent momentum algorithm. The experimental and simulation results show that the proposed scheme is highly efficient [56].

In Ref. [60], the authors presented an algorithm for maximum power point tracking controller for PV systems using neural networks. According to the authors, the experimental results showed that the PV system with MPPT always tracks the peak power point of the PV module under various operating conditions. The MPPT transmits about 97% of the actual maximum power generated by the PV module. The MPPT not only increases the power from the PV module to the load but also maintains longer operating periods for the PV system. The air velocity and the air mass flow rate of the mechanical load are increased considerably due to the increase of the PV system power. It is also found that the increase in the output energy due to the use of MPPT is about 45.2% for a clear sunny day [56].

Bahgata et al. [61] developed and implemented a PC-based maximum power point tracker (MPPT) for PV system using neural networks (NN). The system consists of a PV module via a MPPT supplying a dc motor that drives an air fan. The control algorithm is developed to use the artificial NN for detecting the optimal operating point under different operating conditions, and then the

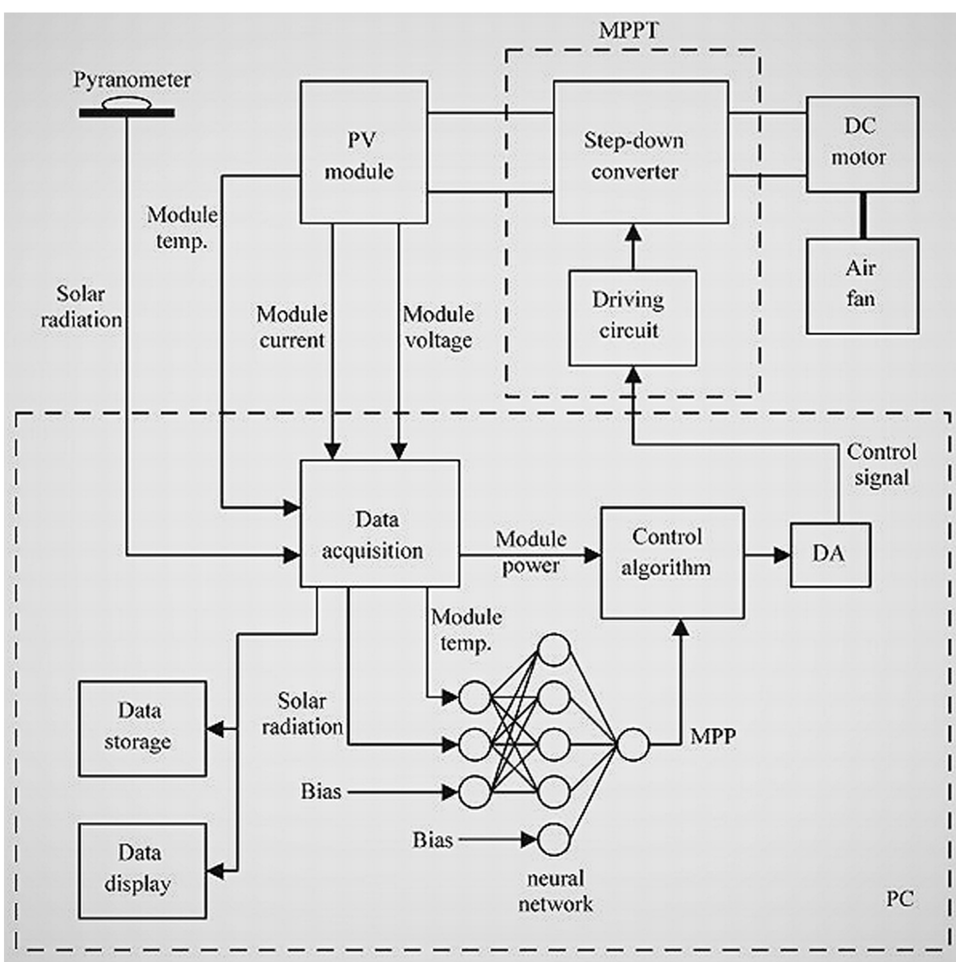


**Fig. 15.** Schematic diagram of the PC-based MPPT for the PV system using neural networks [61].

control action gives the driving signals to the MPPT. A PC is used for data acquisition, running the control algorithm, data storage, as well as data display and analysis. The system has been implemented and tested under various operating conditions. Fig. 15 shows the MPPT for PV system using ANN. Fig. 16 shows the daily percentage increase in the output energy of the PV system by the MPPT during 1 month.

Chaouachi et al. [62] present a novel methodology for Maximum Power Point Tracking (MPPT) of a grid connected 20 kW photovoltaic (PV) system using neuro-fuzzy network. The proposed method predicts the reference PV voltage guaranteeing optimal power transfer between the PV generator and the main utility grid. The neuro-fuzzy network is composed of a fuzzy rule-based classifier and three multi-layered feed forwarded artificial neural networks (ANN). Inputs of the network (irradiance and temperature) are classified before they are fed into the appropriated ANN for either training or estimation process while the output is the reference voltage. The main advantage of the proposed methodology, compared to a conventional single neural network-based approach, is the distinct generalization ability regarding the nonlinear and dynamic behavior of a PV generator. In fact, the neuro-fuzzy network is a neural network-based multi-model machine learning that defines a set of local models emulating the complex and nonlinear behavior of a PV generator under a wide range of operating conditions. Simulation results under several rapid irradiance variations proved that the proposed MPPT method fulfilled the highest efficiency compared to a conventional single neural network and the Perturb and Observe (P&O) algorithm dispositive.

Syafaruddin et al. [63] utilized a radial basis function neural network (RBF-ANN) based intelligent control method to map the global operating voltage and non-irradiance operating condition in string and central based MPPT systems. The proposed method has been tested on 103 (2.2 kW), 153 (2.5 kW) and 203 (3.3 kW) of series–parallel PV array configuration under random-shaded and continuous-shaded patterns. The proposed method is compared with the ideal case and conventional method through a simple power–voltage curve of PV arrays. The simulation results show that there are significant increases of about 30–60% of the extracted power in one operating condition when the proposed method is able to shift the operating voltage of modules to their optimum voltages.

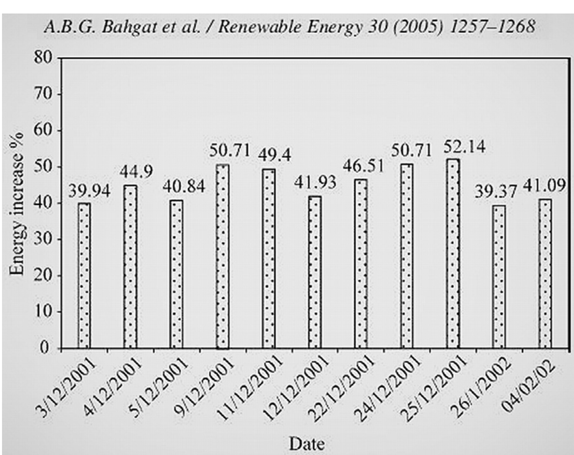


**Fig. 16.** The daily percentage increase in the output energy of the PV system by the MPPT during 1 month [61].

Sedaghati et al. [64] discussed the using of artificial neural network (ANN) for the tracking of maximum power point. Error back propagation method is used in order to train neural network. In this method neural network is used to specify the reference voltage of maximum power point under different atmospheric conditions. By properly controlling DC–DC boost converter, tracking of maximum power point is feasible. To verify theory analysis, simulation result is obtained by using MATLAB/SIMULINK.

Rai et al. [65] have developed the simulation model of an artificial neural network (ANN) based maximum power point tracking controller. The controller consists of an ANN tracker and the optimal control unit. The ANN tracker estimates the voltages and currents corresponding to a maximum power delivered by solar PV (photovoltaic) array for variable cell temperature and solar radiation. The cell temperature is considered as a function of ambient air temperature, wind speed and solar radiation. The tracker is trained by employing a set of 124 patterns using the back propagation algorithm. The mean square error of tracker output and target values is set to be of the order of $10^{-5}$ and the successful convergent of learning process takes 1281 epochs. The accuracy of the ANN tracker has been validated by employing different test datasets. The control unit uses the estimates of the ANN tracker to adjust the duty cycle of the chopper to the optimum value needed for maximum power transfer to the specified load.

Table 6 gives a summary of ANN usage for maximum power point tracking applications of PV systems.

### 3.2. Wind power systems

Power electronic devices have the important role of controlling power of WECS (Wind Energy Conversion Systems). These electronic parts use control schemes to gain maximum performance from WECS. Kanellos et al. [66] presented a new neurocontrol scheme for a variable speed wind turbine (VSWT). A voltage source converter cascade is used by employing neurocontrol for the generator side converter and three independent hysteresis controllers for the grid side. A new method for estimating the optimal rotating speed is also proposed. The repercussions of the connection of a wind park (WP), composed of wind turbines (WTs) of this type, on the operation of weak electric distribution systems are also analyzed. The effects on the voltage profile caused by variable speed (VS) wind turbines are compared to the effects caused by fixed speed (FS) WTs. Both types of WTs are assumed to be equipped with asynchronous machines. The advantages of the studied VS operation scheme are confirmed and the possible

**Table 6**
List of ANN usage for maximum power point tracking applications of PV systems.

| No. | Subject | Year | Ref. no. |
|---|---|---|---|
| 1 | Neural network-based estimation of maximum power generation from PV module using environmental information | 1997 | [57] |
| 2 | ANN-based peak power tracking for PV supplied dc motors | 2000 | [55] |
| 3 | A robust control method for a PV supplied DC motor using universal learning networks | 2004 | [58] |
| 4 | Artificial neural network maximum power point tracker for solar electric vehicle | 2005 | [59] |
| 5 | Maximum power point tracking controller for PV systems using neural networks | 2005 | [60] |
| 6 | Maximum power point tracking controller for PV systems using neural networks | 2005 | [61] |
| 7 | Artificial intelligence techniques for photovoltaic applications: a review | 2008 | [56] |

increase in the installed capacity of the WP over the FS mode, maintaining the same power quality standards, is estimated.

Miller et al. [67] proposed a simple control scheme that will allow an induction motor to run a turbine at its maximum power coefficient. The control uses a standard V/Hz converter and controls the frequency to achieve the desired power at a given turbine speed.

Papathanassiou et al. [68] presented a brief review of common electrical generation schemes for wind turbines (WTs) and photovoltaics (PVs). Attention is mainly focused on the power converter interfaces used for the grid connected operation of the renewable generators. The WT soft starting arrangements are described and the most common variable speed operation configurations are presented and discussed. The fundamental characteristics and requirements of the power conditioning equipment used in PVs are outlined and the power converters of certain PV generators are briefly presented.

Abdin et al. [69] presented the modeling and control design for a wind energy conversion scheme using induction generators. The scheme consists of a three-phase induction generator driven by a horizontal axis wind turbine and interfaced to the utility through a double overhead transmission line. A static VAR compensator was connected at the induction generator terminals to regulate its voltage. The mechanical power input was controlled using the blade pitch angle. Both state and output feedback controllers are designed using MATLAB software to regulate the generator output. From the simulation results, the response of closed loop system exhibited a good damping and fast recovery under different types of large disturbances.

Nikham et al. [70] studied on a multiobjective daily volt/var control (MDVVC) for radial distribution feeders integrated renewable energy sources (RES) by means of the tap position of the under load tap changer (ULTC) transformers, shunt capacitors, and active and reactive powers of RES. The multiple objective functions to be minimized are the electrical energy losses, the voltage deviations, and the total emissions of RES and substations. Discrete behavior of equipment in the distribution systems and nonlinear power flow equations change the VVC problem into a mixed integer nonlinear programming (MINLP). Hence, a new optimization method based on the shuffled frog-leaping algorithm (SFLA) is presented to solve the optimization problem. The SFLA is modified for resolving the disadvantages of the original algorithm. Besides accurately passing local optima, the MSFLA takes less time to achieve the optimal response. Furthermore, the tribe-MSFLA is proposed through using the concept of the tribe. Dealing with the multiobjective optimization problem, an interactive fuzzy satisfying method is used while the objective functions are formulated by a fuzzy set theory. An 85-bus radial distribution system is used to test and assess the performance of the proposed algorithm.

Ghasemi et al. [71] presented an overview of subsynchronous resonance issues in wind turbines including analysis methods, modeling, the impact of control parameters, and the proposed mitigation methods. Much of this study is focused on variable speed wind turbines.

Rabiee et al. [72] published a review of various storage systems for wind power applications. The introduction of the operating principles, the presentation of the main characteristics of energy storage systems suitable for stationary applications, and the definition and discussion of potential ESS applications in wind power are examined according to an extensive literature review.

Kanellos et al. [73] designed a new neurocontrol scheme for a variable speed wind turbine. Neural network for the induction machine of the wind Turbine is shown in Fig. 17. Active power produced by the generators and injected to the grid for low wind speed is shown in Fig. 18.

Ro et al. [74] have designed a neural network (NN) pitch controller of a grid connected wind turbine system for extracting maximum power from wind and prove that its performance using the NN controller would be better than using a classical PI controller. Figs. 19 and 20 show the configuration of the grid connected wind turbine system and model for the neural network pitch angle controller diagram. The following steps were conducted in this study:

(a) In the low wind speed region, maximum power coefficient operating mode is adapted to obtain the optimal power as long as possible.
(b) In the higher wind speed region, the pitch angle is controlled to bypass the excess energy in the wind and the output power is kept nearly constant.
(c) The NN pitch controller exhibits better performance than a PI controller in the maximum power extraction from wind.

Mayosky et al. [75] discussed the application of Gaussian networks in the implementation of adaptive controllers for WECSs. The approach used, based on a combination of Gaussian networks and a sliding mode supervisor controller, allowed fast

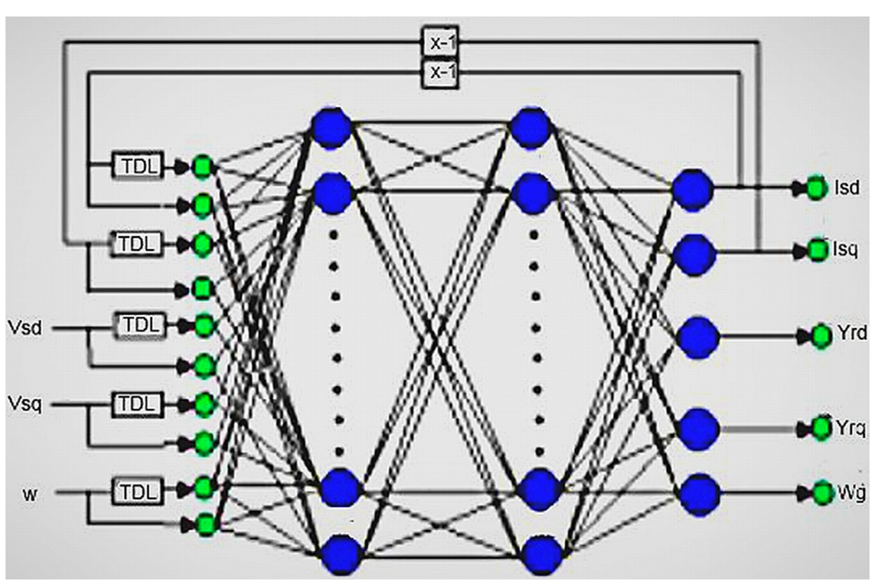


**Fig. 17.** Neural network for the induction machine of the wind turbine [73].

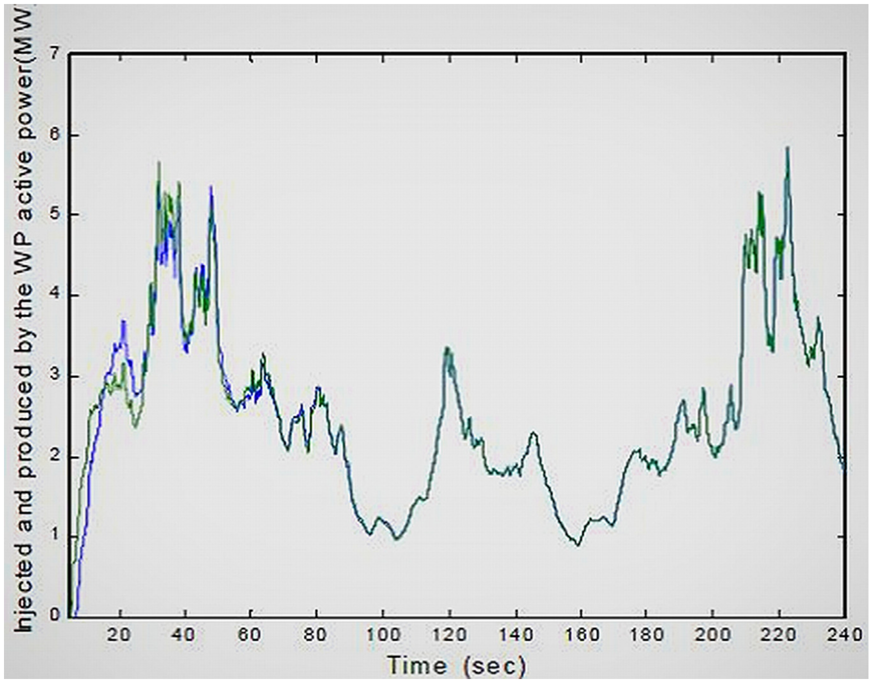


**Fig. 18.** Active power produced by the generators and injected to the grid for low wind speed [73].

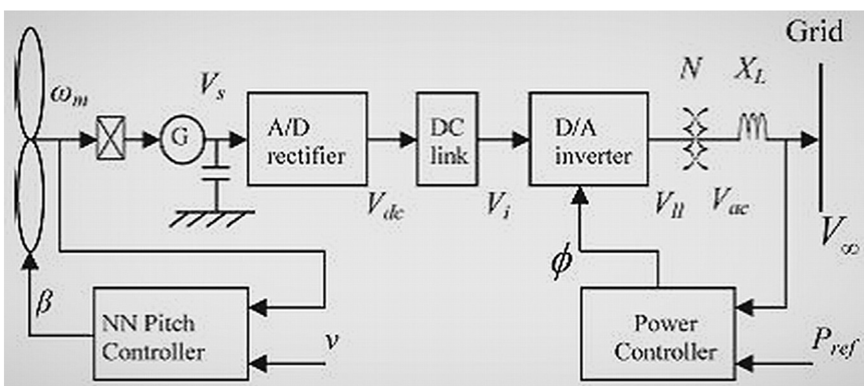


**Fig. 19.** Configuration of the grid connected wind turbine system [74].

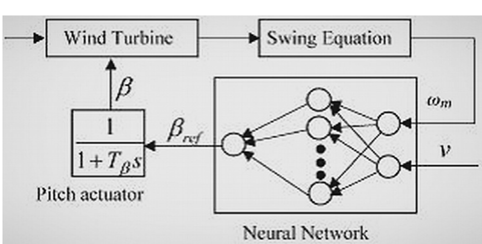


**Fig. 20.** Model for the neural network pitch controller [74].

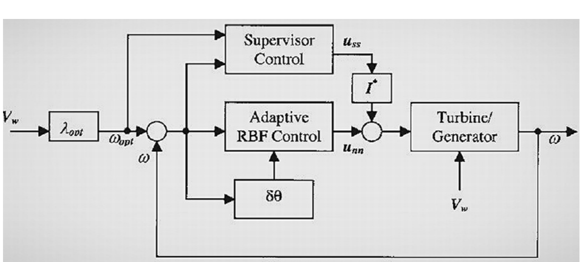


**Fig. 21.** Closed loop block diagram of wind turbine control system. It includes a supervisor control block and an adaptive radial basis function (RBF) control block [75].

convergence to a simple linear dynamic behavior, even in the presence of parameter changes and model uncertainties. The resulting controller shown to be simple enough to be synthesized using fixed-point signal processors.

Fig. 21 shows the controller scheme for wind turbine system which includes an adaptive controller and a supervisor controller. Fig. 22 shows the system response for a pseudoaleatory sequence of wind gusts. As shown in the figure, ANN control system converges to the first-order system dynamic.

Li et al. [76] used a small wind generation system where neural network principles are applied for wind speed estimation and robust control of maximum wind power extraction against potential drift of wind turbine power coefficient curve. Fig. 23 shows proposed training scheme for ANN-based wind velocity estimation. Fig. 24 shows the results of simulation. Compared to the traditional control strategies, the new method has the following features:

1. A maximum mechanical power of the wind turbine can be well tracked at both dynamic and steady states.
2. A neural network-based wind velocity estimator is developed to provide fast and accurate velocity information to avoid using anemometers.

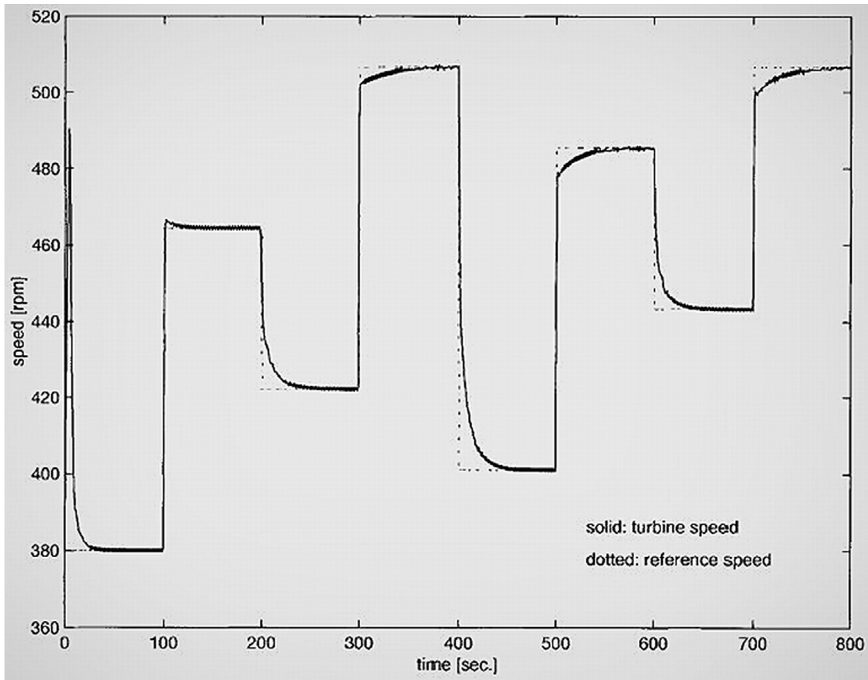


**Fig. 22.** Closed loop system response to a pseudoaleatory sequence of wind gusts. System response converges to the desired first-order dynamics [75].

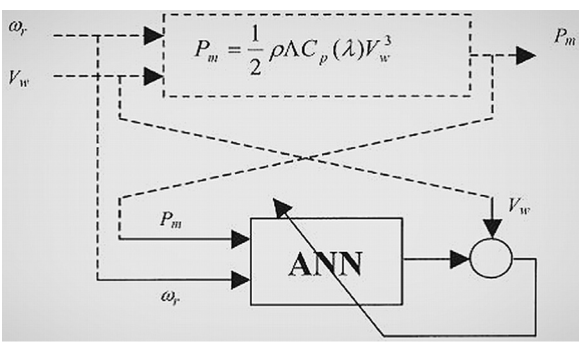


**Fig. 23.** Proposed training scheme for ANN-based wind velocity estimation [76].

3. A neural-network-based scheme is presented to compensate the potential drift of wind turbine power coefficient without extra sensors.

Kélouwani et al. [77] have described a nonlinear model of wind turbine based on a neural network (NN) for the estimation of wind turbine output power. The proposed nonlinear model uses the wind speed average, the standard deviation and the past output power as input data. An anemometer with a sampling rate of 1 s provides the wind speed data. The optimal NN configuration is found to be 8–5–1 (8 inputs, 5 neurons on the hidden layer, one neuron on the output layer). The estimated mean square errors for the wind turbine output power are calculated less than 1% (Fig. 24).

Fig. 25 shows the neural network configuration for parameters identification. As shown in the figure, a NN weight update process is used for parameter identification. Fig. 26 shows the MSE (mean square error) between the estimated and the measured test data with NN model.

In Yilmaz et al. [78], a satisfactory controller, incorporated in the system, is developed by using an artificial neural network. Multilayer perceptron (MLP) and radial basis function (RBF) are used and compared as pitch angle controllers. The output power and rotational speed are successfully limited at the rated values during the over-speed wind conditions. The main advantages of the proposed controllers are that it is easily adaptable for different conditions and that it has fast reply capability.

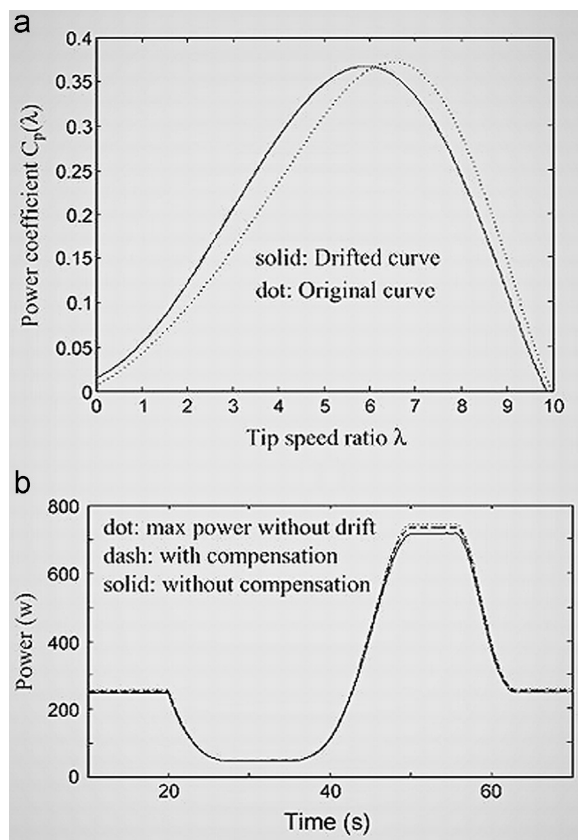


**Fig. 24.** Simulation results. (a) Power coefficient with drift error. (b) Turbine output power without compensation (average error = 10.7738) and with compensation (average error = 4.2426) [76].

Figs. 27–29 show the neural network controllers (MLP and RBF), block diagrams and the simulation results for trained

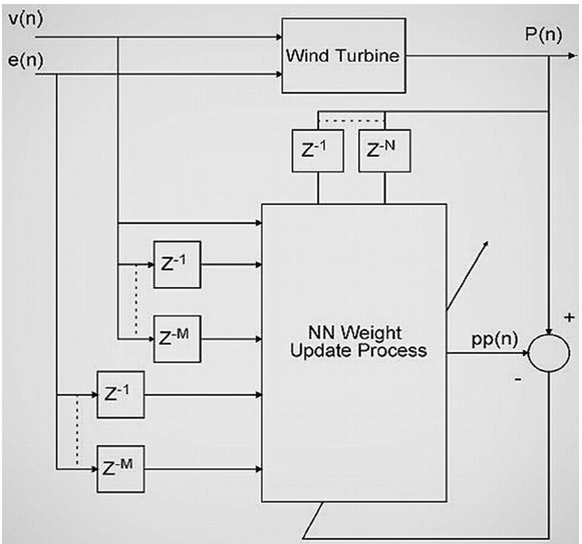


**Fig. 25.** NN configuration for parameters identification [77].

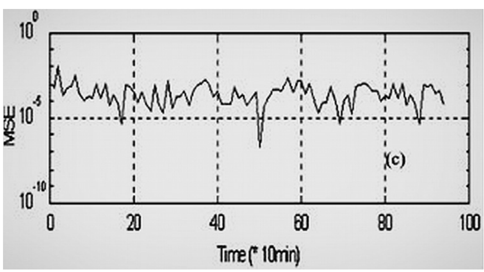


**Fig. 26.** The mse (mean square error) between the estimated and measured test data with NN model [77].

networks. The network errors have given simulation results that show that neural network controller's error goes to zero in steady state response.

Koutroulis et al. [79] have described an alternative approach for WG maximum power-point-tracking (MPPT) control. The block diagram of the proposed system is illustrated in Fig. 30. The MPPT process is based on monitoring the WG output power using measurements of the WG output voltage and current and directly adjusting the dc/dc converter duty cycle according to the result of comparison between successive WG output power values.

There are a few other studies about maximum power point tracking on wind energy conversion systems (WECS) [80,81]. Table 7 gives a summary of ANN usage for wind power systems.

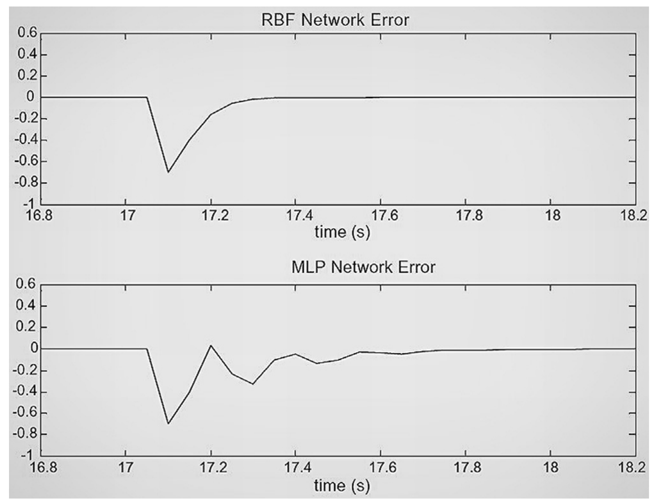


**Fig. 29.** Trained neural network errors between $t$=16.8 and 18.2 s [78].

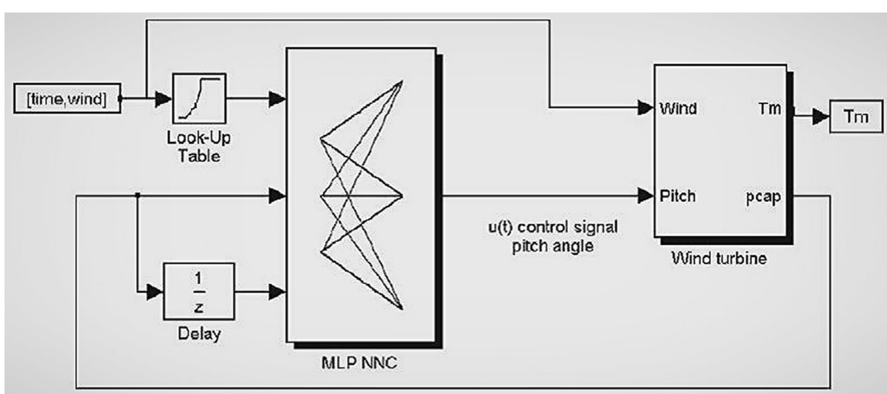


**Fig. 27.** Block diagram of proposed MLP-NNC [78].

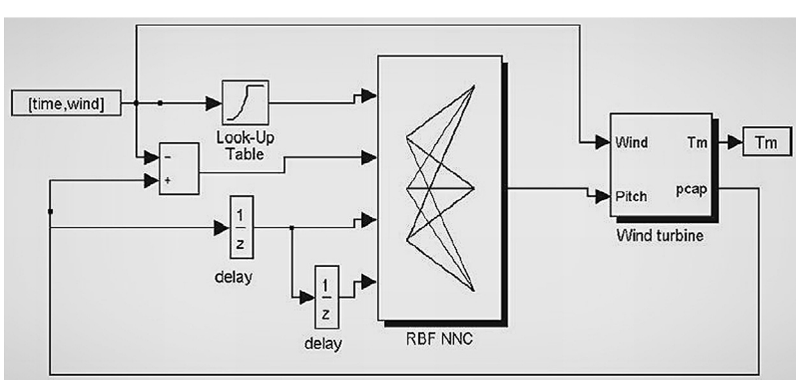


**Fig. 28.** Block diagram for proposed RBF-NNC [78].

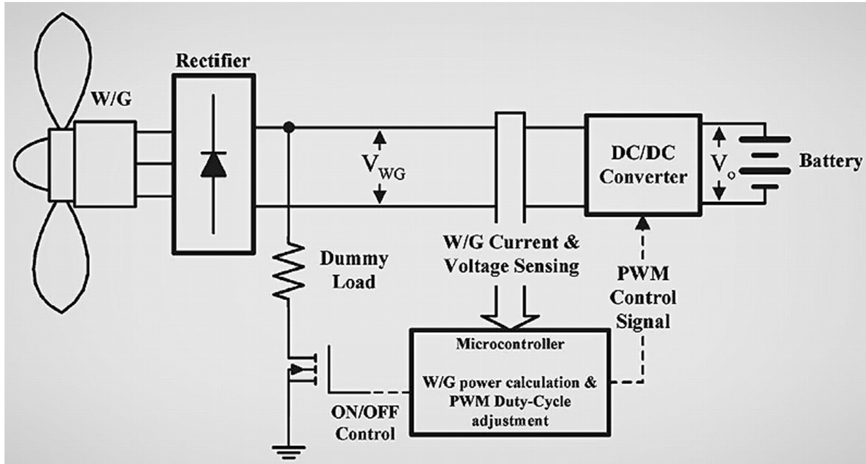


**Fig. 30.** Block diagram of the proposed system [79].

**Table 7**
List of ANN usage for wind power systems.

| No. | Subject | Year | Ref. no |
|---|---|---|---|
| 1 | Direct adaptive control of wind energy conversion systems using Gaussian networks | 1999 | [75] |
| 2 | A new control scheme for variable speed wind turbines using neural networks | 2002 | [73] |
| 3 | A new maximum power point tracking control scheme for wind generation | 2002 | [80] |
| 4 | Nonlinear model identification of wind turbine with a neural network | 2004 | [77] |
| 5 | Application of neural network controller for maximum power extraction of a grid connected wind turbine system | 2005 | [74] |
| 6 | Neural-network-based sensorless maximum wind energy capture with compensated power coefficient | 2005 | [76] |
| 7 | Design of a maximum power tracking system for wind-energy-conversion applications | 2006 | [79] |
| 8 | Wind speed estimation based sensorless output maximization control for a wind turbine driving a DFIG | 2008 | [81] |
| 9 | Pitch angle control in wind turbines above the rated wind speed by multi-layer perceptron and radial basis function neural networks | 2009 | [78] |

### 3.3. Hybrid power systems

Neural network applications for hybrid power systems are divided into two parts: control of autonomous hybrid power systems and control of grid connected hybrid power systems.

#### 3.3.1. Control of autonomous hybrid power systems

It is estimated that billions of people in small remote villages especially in developing countries currently lack grid-based electricity service. In many cases, grid extension is impractical because of dispersed populations, rugged terrain, high cost of transmission lines and higher transmission losses associated with the distribution of centrally generated power to remote areas. A stand-alone, off-grid renewable energy system is an important option for narrowing the electricity gap in rural parts of the developing world [82].

Kumaravel et al. [83] have designed an overall power management strategy for a stand-alone wind–PV hybrid system to manage power flows among the different energy sources, the storage unit and loads in the system. A simulation model for the hybrid energy system has been developed using MATLAB/Simulink. The system performance under different scenarios has been verified by carrying out simulation studies using a practical load demand profile and real weather data.

Fig. 31 shows the overall control scheme of intelligent power management controller. As it is shown in figure, there are two neural network structures for PV and wind power systems which control power flow primary load and deferrable load. Fig. 32 shows the simulation result of delivered renewable power and load demand of the proposed system on a typical day.

Fargli et al. [84] have developed a control system, which includes the Neural Network Controller (NNC) for achieving the coordination between the components of a PV–wind hybrid system as well as controlling the energy flows.

During this operation of the hybrid PV/wind system, different situations may appear:

1. The total current generated by the PV and wind generators is greater than the current needed by the load. In this case, the energy surplus is stored in the batteries and the controller puts the battery in charge condition. When the battery SOC reaches a maximum value, the control system stops the charging process [84].
2. The total PV and wind generator current is less than the current needed by the load, the energy deficit is covered by the storage and the controller puts the battery in the discharge condition. If the battery capacity decreases to their minimum level, the control system disconnects the load and the energy deficit [84].
3. In case of inverter input and total power equality, the storage capacity remains unchanged [84].

Fig. 33 shows proposed neural network control system. Neural network controller tries to control power flow through PV and wind generators to load. Fig. 34 shows the current generating with NNC over the simulation period. NNC had success in tracking the reference load [84].

Lin et al. [85] proposed a stand-alone hybrid power system. The system consists of solar power, wind power, diesel engine, and an intelligent power controller. MATLAB/Simulink was used to build the dynamic model and simulate the system. To achieve a fast and stable response for the real power control, the intelligent controller consists of a radial basis function network (RBFN) and an improved Elman neural network (ENN) for maximum power point tracking (MPPT). The pitch angle of wind turbine is controlled by the ENN, and the solar system uses RBFN, where the output signal

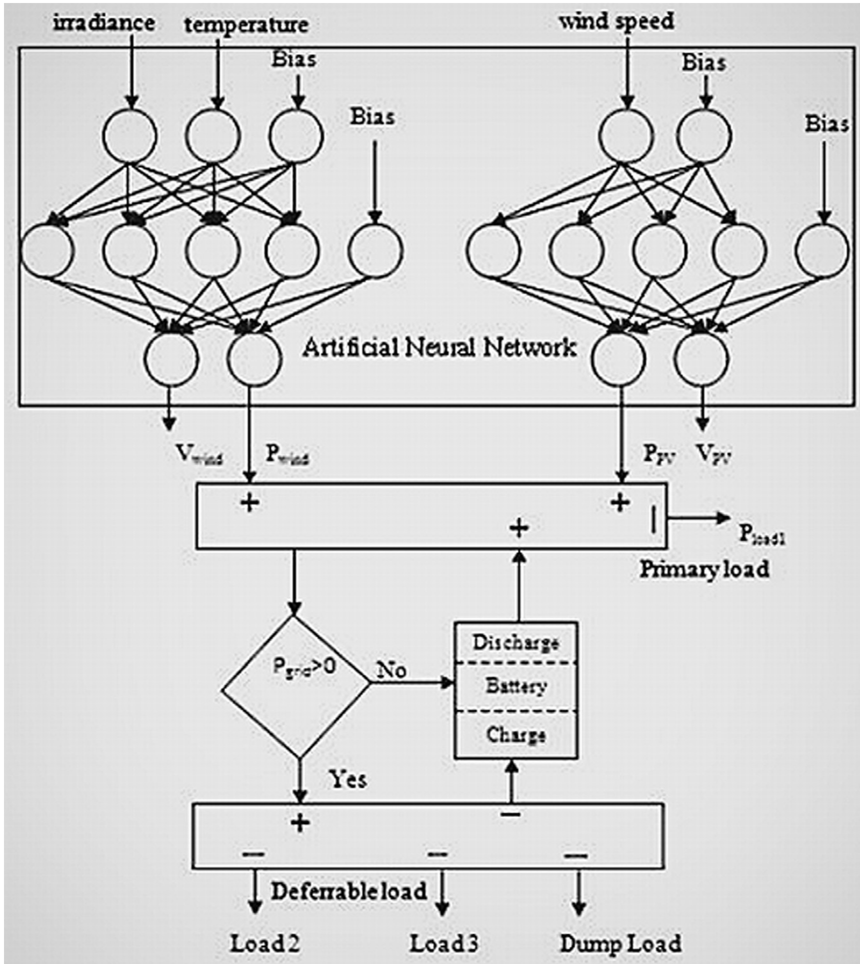


**Fig. 31.** Block diagram of the overall control scheme of intelligent power management controller [83].

is used to control the dc/dc boost converters to achieve the MPPT. Fig. 35 shows the proposed system.

Table 8 shows performance comparison of the Elman type neural network and conventional PI controller for wind turbine part of hybrid power system. As shown in the table, ENN controller has better performance than PI controller.

A radial basis function network is used to track maximum power point for PV module of hybrid system. Also P&O algorithm is used for the same purpose. Fig. 36 shows the comparison between RBFN network and P&O algorithm for MPPT of PV system. As showns in figures, radial basis function network has better performance while tracking maximum power point of PV sub-module of stand-alone hybrid system [85].

In another study, Farghally et al. [86] presented the sizing of a complete PV–wind hybrid system for supplying electricity to emergency hospital, school and home buildings according to their energy requirements. The computer program (HOMER Pro.) solves the optimization problem to minimize the objective function considering the different constraints and providing the optimum wind, solar and battery ratings. Also, a neural network controller is developed for achieving the coordination between system components as well as controlling the energy flows Fig. 36).

Ali Al-Alawi et al. [87] discussed the development of a predictive artificial neural network (ANN)-based prototype controller for the optimum operation of an integrated hybrid renewable energy-based water and power supply system (IRWPSS). The integrated system, which has been assembled, consists of photovoltaic modules, diesel generator, battery bank for energy storage and a reverse osmosis desalination unit. The electrical load consists of typical households and the desalination plant. The proposed artificial neural networking controller is designed to be implemented to take decision on diesel generators ON/OFF status and maintain a minimum loading level on the generator under light load and high solar radiation levels and maintain high efficiency of the generators by switching off diesel generator when not required based on predictive information. The key objectives are to reduce fuel dependency, engine wear and tear due to incomplete combustion and cut down on greenhouse gas emissions. The statistical analysis of the results indicates that the R2R2 value for the testing set of 186 cases tested was 0.979. This indicates that ANN-based model developed in this work can predict the power usage and generator status at any point of time with high accuracy.

### 3.3.2. Control of grid connected hybrid power systems

Grid connected hybrid power systems generate power and transfer generated power to directly interconnected network. So, power generation and power demand are important factors for controlling the amount of generated power and power flow such as these types of systems. Neural network-based controllers are able to control both power generation and power flow controls. There are few studies in this area for controlling ac grid connected wind–PV power systems with artificial neural network structures.

Younsi et al. [88] proposed a hybrid renewable energy system which collects wind generator (WG) with diesel generator (DG), and flywheel energy storage system (FESS). The unit is based on permanent magnet synchronous machines (PMSM). The hybrid

system is connected to AC network by using power electronic. Control methods for each subsystem have developed (wind generator, diesel generator, flywheel energy storage system) and the sliding mode control has been applied for the permanent magnet synchronous machine; it is a robust method for very disturbed models and it can be well chosen for wind renewable energy systems of production which are very fluctuating in very short

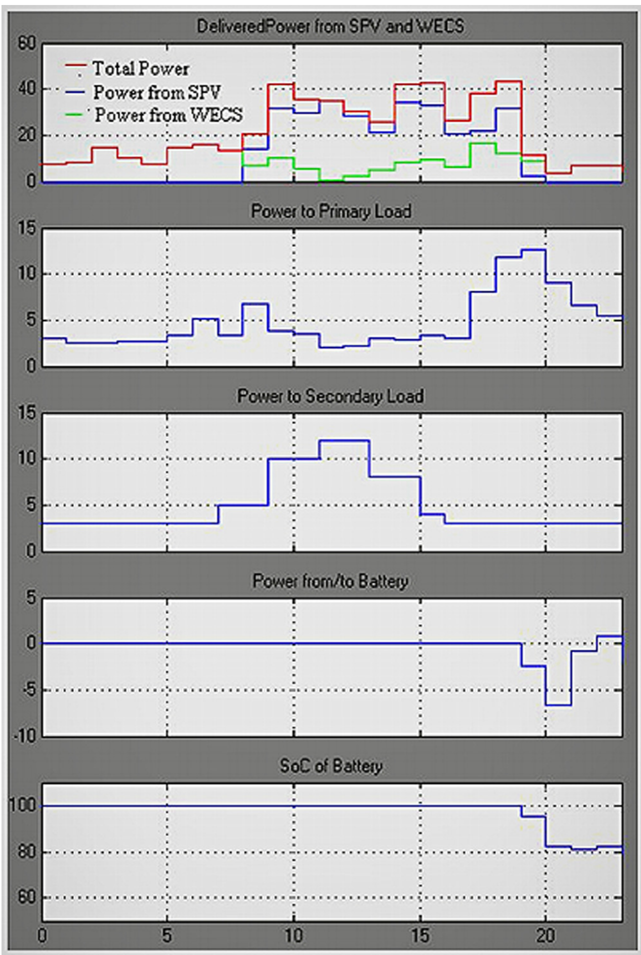


**Fig. 32.** Simulation result of delivered renewable power and load demand of the proposed system on a typical day [83].

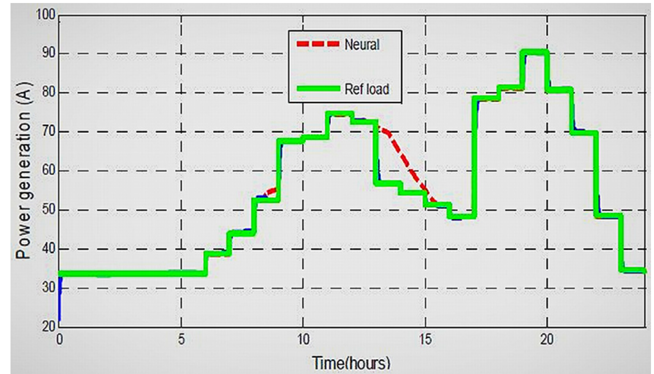


**Fig. 34.** Current generating with NNC over the simulation period [84].

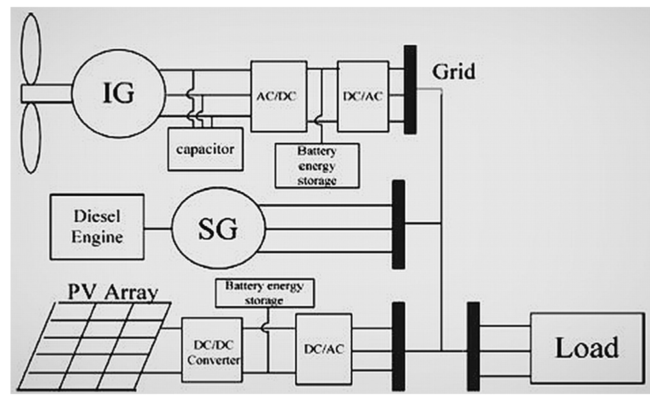


**Fig. 35.** Proposed hybrid system [85].

**Table 8**
Performance comparison of the ENN and PI controller [85].

| Controller type | Wind speed (m/s) | Power coefficient (Cp) | Pitch angle (deg) | Average power (kW) |
|---|---|---|---|---|
| ENN | 12 | 0.482 | −0.7 | 1.88 |
| | 8 | 0.481 | −0.8 | 0.22 |
| PI | 12 | 0.465 | −0.55 | 1.77 |
| | 8 | 0.37–0.42 | −0.2 to −0.55 | 0.03 |

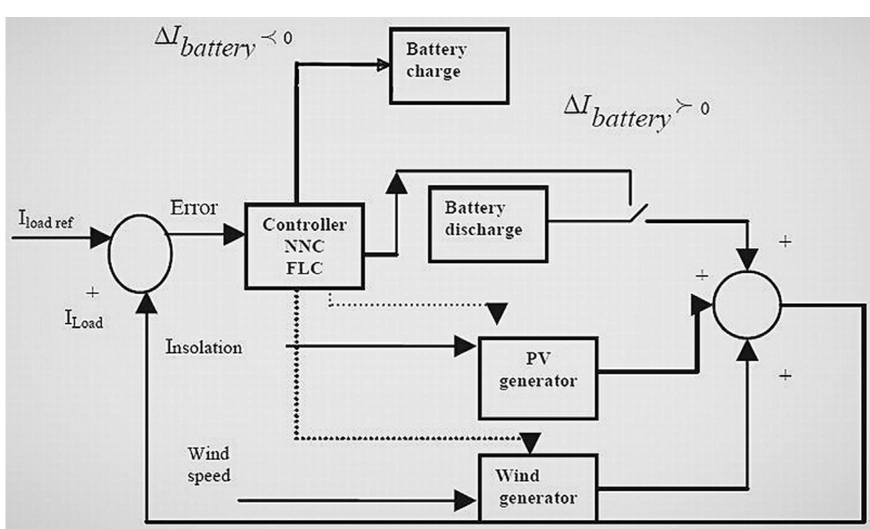


**Fig. 33.** Proposed control system of the hybrid PW/wind system [84].

time. The system control also requires the development of a supervisor. This supervisor based on artificial neural network (ANN) model decides the energy transfer type of flywheel energy storage system (charging/discharging/no transfer energy) and takes decision on diesel generators ON/OFF status. These two parameters are selected to determine the control mode of the machine of the flywheel energy storage system (motor/generator/not controlled) and to control the intervention of diesel generator. Fig. 37 shows the proposed hybrid renewable energy system configuration

Fig. 38 shows the reference power signal and generated power by hybrid power system. It is shown in figure that neural network controller works well while tracking reference power signal.

El-Tamaly et al. [89] have designed a computer program to determine the optimum number of PV modules and optimum number of wind turbine generator, WTG based on maximum power point by using neural network for the system under study. The computer program can completely design the hybrid system and determine the hourly system parameters as power flow, frequency of output power from WTG, and DC output voltage from PV modules.

Fig. 39 shows the flowchart of the proposed computer program. The program reads solar irradiance, temperature, and wind speed data. Then, it tries to calculate maximum power for one PV module and wind turbine generator. Then, it tries to decide optimum number of PV modules and wind turbine generators (WTG).

Giraud et al. [90] have modeled a grid connected hybrid power system that consists of a wind turbine and a PV module. The system is modeled with ANN. Since system parameters need not be known, the ANN modeling drastically reduces computational complexity and model uncertainty. Non-linearity, known and unknown dynamics are captured and stored in the weights of the layer interconnections. For a short time period, the wind and the irradiance are considered as the sole sources of power, and the goal is to calculate system responses as they vary. Fig. 40 shows the schematic of the utility-interactive wind–PV system (WPS) with storage unit.

Fig. 41 shows the setup of the recurrent neural network (RNN) for training. Table 9 shows above the correlation and error between simulates and actual values. According to the table, regression and error results show that the performance of neural network controller is acceptable for these types of hybrid renewable systems.

Table 10 shows the summary of ANN usage for wind–PV hybrid power systems.

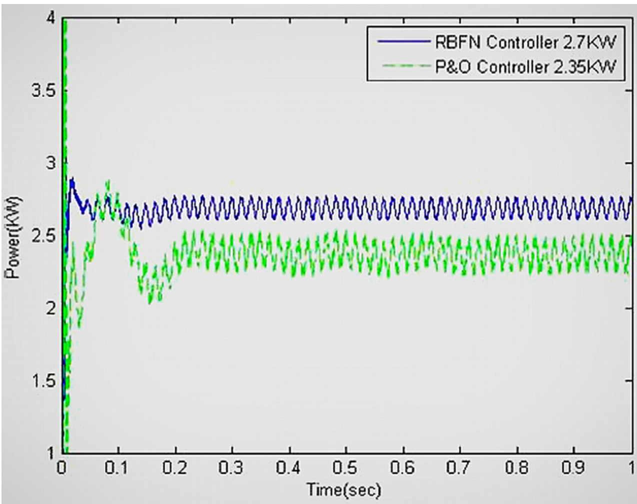


**Fig. 36.** MPPT tracking response of the PV system. [85].

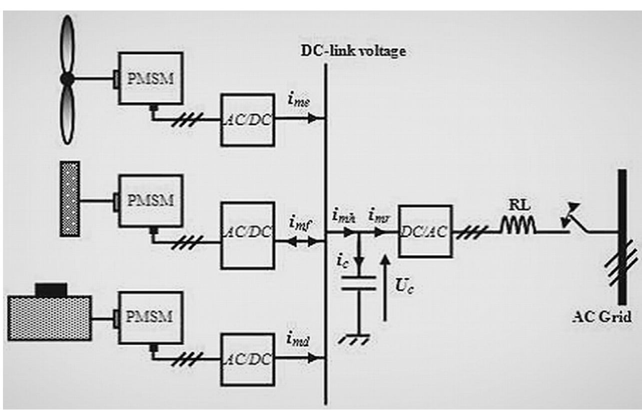


**Fig. 37.** Hybrid renewable energy system configuration [88].

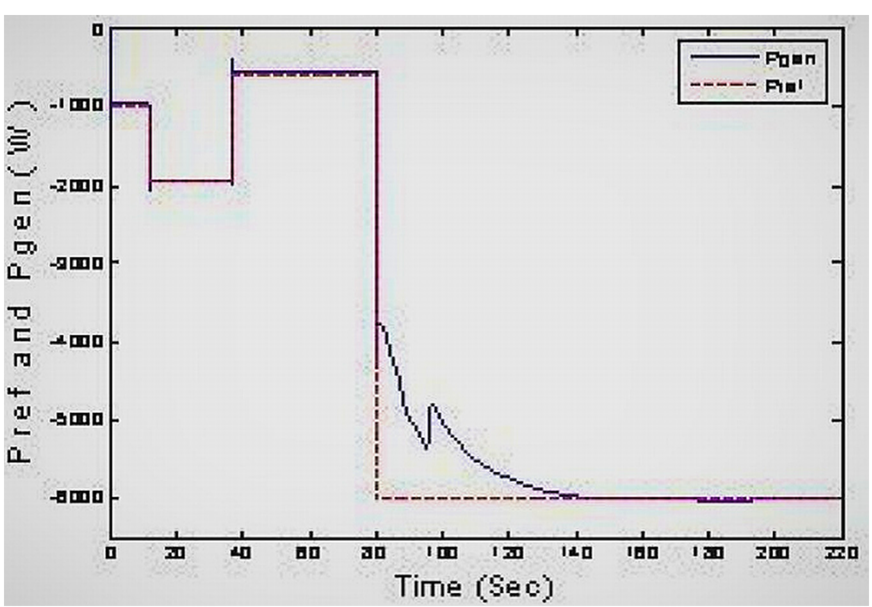


**Fig. 38.** Reference power and generated power [88].

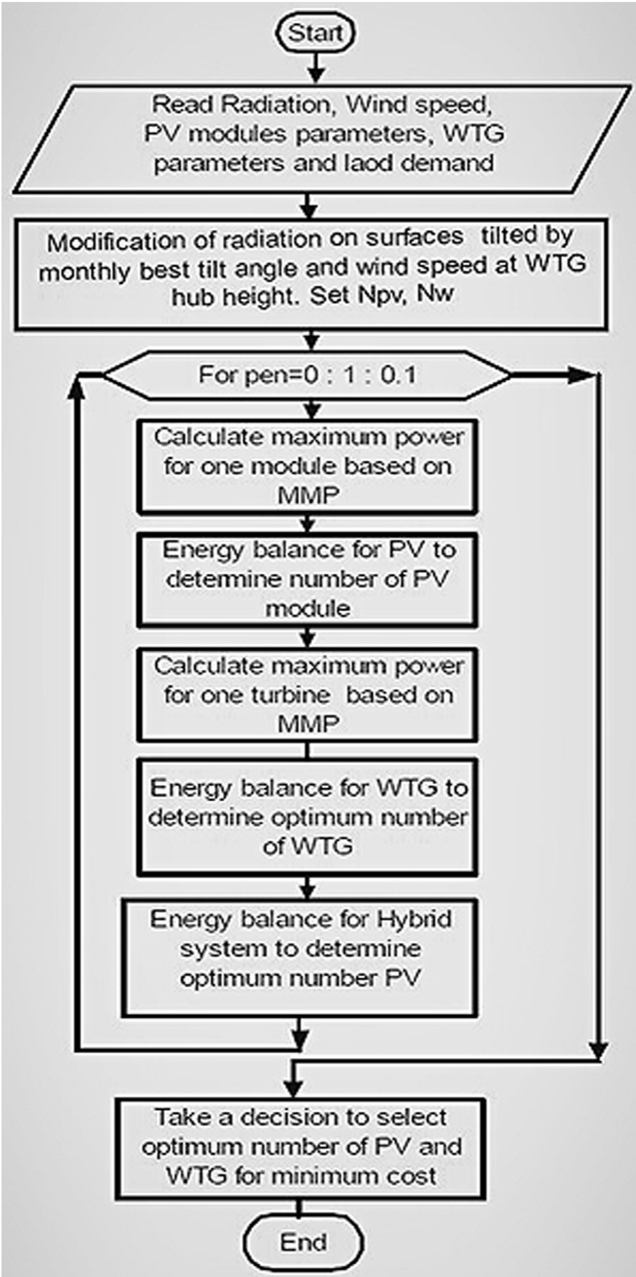


**Fig. 39.** Flowchart of the proposed computer program [89].

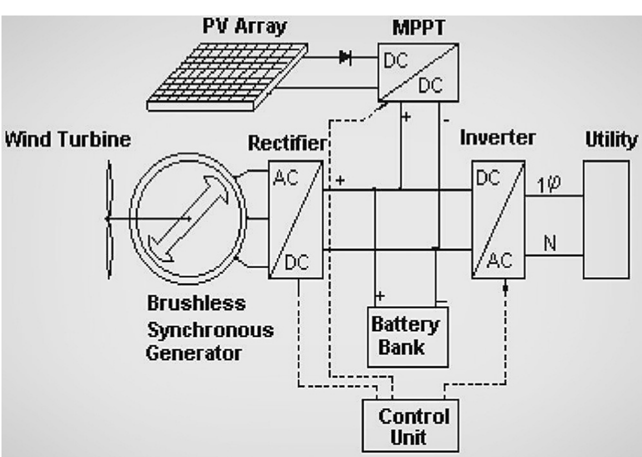


**Fig. 40.** Schematic of the utility-interactive WPS with storage unit [90].

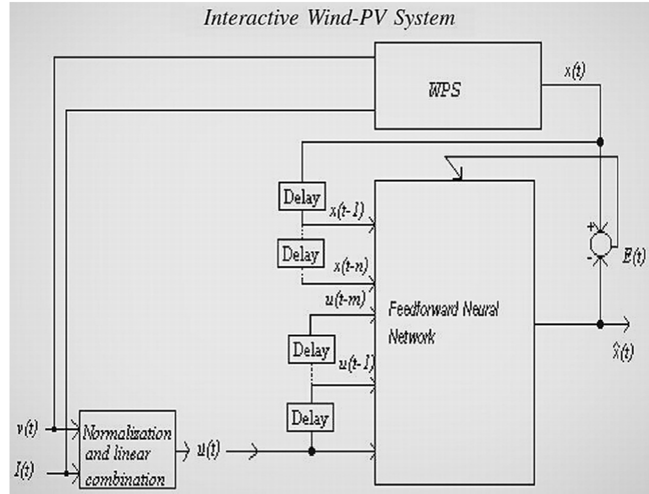


**Fig. 41.** Setup of the recurrent neural network (RNN) for training [90].

**Table 9**
Correlation and error between simulated and actual values [90].

| | Correlation | | Standard error | |
|---|---|---|---|---|
| | Regression | Neural networks | Regression (W) | Neural networks (W) |
| Hybrid power | 0.9425 | 0.9989 | 261 | 36 |
| Battery power | 0.9219 | 0.9944 | 260 | 74 |

## 4. Discussion

In this section, potential challenges in control of wind, photovoltaic and hybrid power systems are expressed. Unsatisfactory aspects of conventional control methods are evaluated. Countering to the conventional control methods, artificial neural network control approach is suggested as a solution for prospect challenges. Advantages and disadvantages of artificial intelligence techniques are discussed and new trends on power system control methods are handled.

### *4.1. Potential prospect challenges in control of wind, PV and hybrid power systems*

The most encountered problem in control of renewable power systems is controller response to environmental changes. For PV systems, changes of solar irradiance during day affect the efficiency of the system. Especially during summer times and winter times solar irradiance is different. So, control system should handle the changes of solar irradiance due to control output voltage for maximum power point tracking. For conventional control systems, control parameters must be updated manually according to the changing environmental conditions.

Wind speed is changing stochastically. Conventional control systems try to watch changes in wind speed. They do not have prediction and interpretation capability. So, there is a delay while conventional control systems trying to track maximum power for wind power systems. This issue reduces system efficiency. Wind direction is another problem for conventional wind power control systems. Propeller of wind turbine must turn to wind direction for best performance. But wind direction sensors using conventional control systems do not response fast enough to catch the direction of wind. Also, there is delay between actual wind direction and response of conventional control systems.

**Table 10**
List of ANN usage for wind–PV hybrid power systems.

| No. | Subject | Year | Ref. no. |
|---|---|---|---|
| *Autonomous hybrid power systems* | | | |
| 1 | Predictive control of an integrated PV–diesel water and power supply system using an artificial neural network | 2007 | [87] |
| 2 | Optimal operation of biomass/wind/PV hybrid energy system for rural areas | 2009 | [82] |
| 3 | Artificial intelligence techniques for controlling PV–wind powered rural zone in Egypt | 2009 | [84] |
| 4 | Adapted multilayer feedforward ANN-based power management control of solar photovoltaic and wind integrated power system | 2011 | [83] |
| 5 | Neural-network-based mppt control of a stand-alone hybrid power generation system | 2011 | [85] |
| 6 | Control and optimal sizing of PV–wind powered rural zone in Egypt | 2011 | [86] |
| 7 | Neural-network-based MPPT control of a stand-alone hybrid power generation system | 2011 | [87] |
| *Grid connected hybrid power systems* | | | |
| 1 | Design and control strategy of utility interfaced PV/WTG hybrid system | 2003 | [89] |
| 2 | Combined effects of passing clouds and wind gusts on an interactive wind–PV system with battery storage using neural networks | 2007 | [90] |
| 3 | Artificial neural network control of hybrid renewable energy system connected to ac grid | 2011 | [91] |

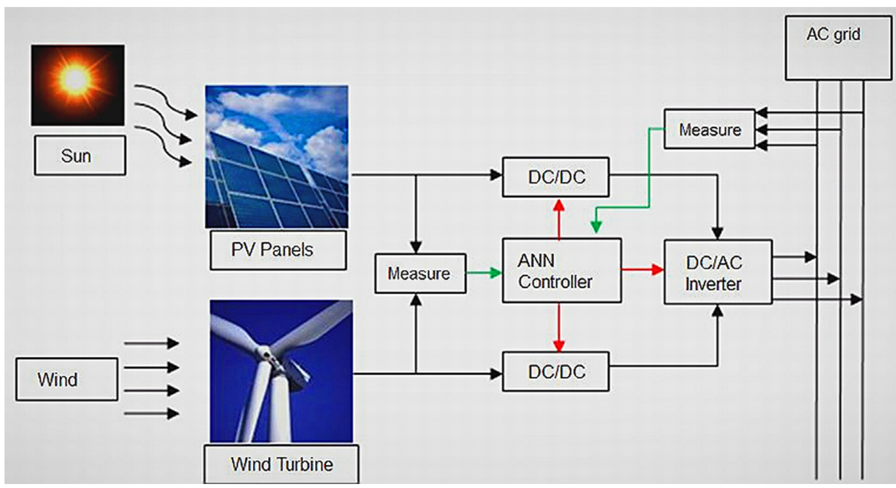


**Fig. 42.** Proposed hybrid power system [91].

For hybrid power systems, control system decides generation percentages of each power generation module due to environmental conditions and power demand. Conventional control systems are slow to track power demand and environmental conditions. So, wrong generation modules work on wrong generation percentages. For autonomous hybrid power systems, battery level should be controlled. Classical control methods only detect battery level. If battery level is under limit, the system is forced to charge the battery and if the battery is full, the system is forced to stop generation and gives permission to power consumption from battery by controller. Classical controllers do not calculate battery life, and they do not estimate time for full charge of battery. Also, they do not calculate load conditions and when the battery is going to be empty. These issues cause unwanted disengages of hybrid power systems from load.

Stabilization of output voltage is another important point, especially grid connected power systems; output voltage must be equal to interconnected grid voltage. Sometimes it is not possible to stabilize output voltage by conventional control methods due to environmental conditions and change of loads. This reduces the power quality in interconnected network.

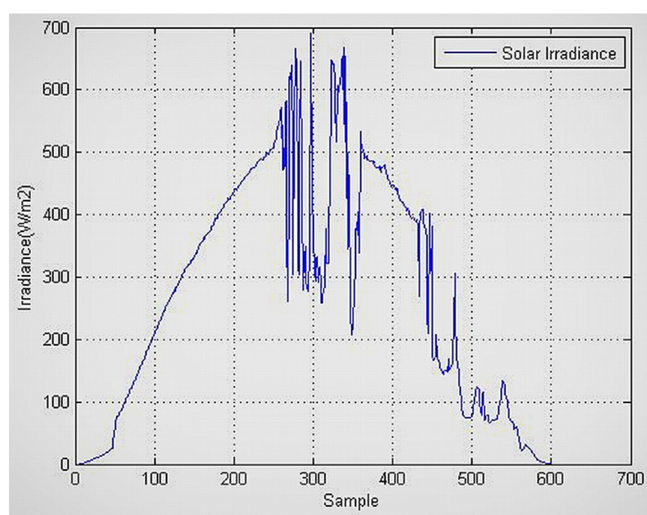


**Fig. 43.** Change of solar irradiance for a cloudy day of Bornova/Izmir [91].

### 4.2. Solutions for potential prospect challenges

Artificial intelligence techniques can create a solution to prospect challenges in the area. In the above sections, artificial neural network controllers are presented for solutions of most of the prospect challenges in wind and photovoltaic power systems. For photovoltaic systems, artificial neural networks are used for modeling of photovoltaic arrays, prediction of solar irradiance and maximum power point tracking applications. For wind power systems, artificial neural networks are used for controlling pitch angle and tracking maximum power point.

Artificial intelligence techniques can propose a solution for tracking maximum power point even when environmental conditions change. Because artificial intelligence techniques have the capability of interpretation and prediction, delays and differences between actual and predicted values can be decreased to minimum levels with these types of control systems.

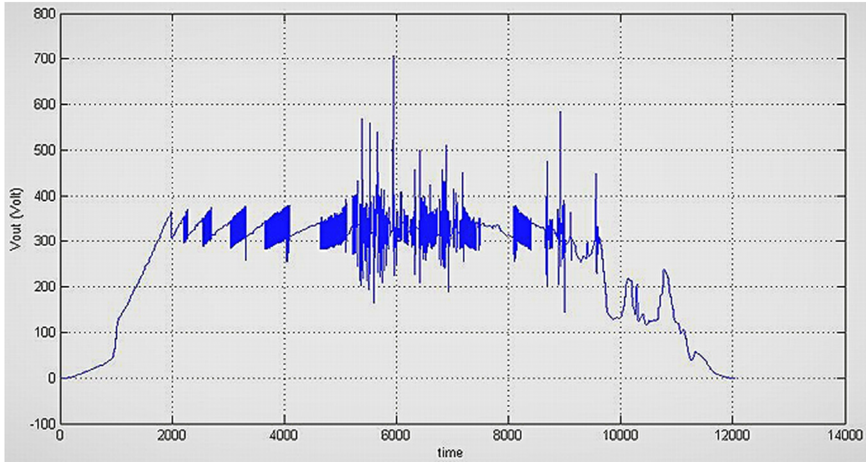

**Fig. 44.** Output voltage when classical closed loop controller used [91].

On the other hand, with today's technology, artificial neural network control structures can be embedded into microchips. It does not increase the total cost of renewable power systems. They can quickly implement to a conventional control system.

However, as shown in Table 9, there are not many applications on controlling hybrid power systems by artificial neural networks. Most of the studies in this area are simulation based. More applications should be studied for improving artificial neural network control systems.

For grid connected hybrid power systems, it is important to stabilize output voltage. A study for controlling PV subsystem of a hybrid power system is given as Ref. [91]. Fig. 42 shows the proposed grid connected hybrid power system. The system consists of PV panels and a wind turbine. An artificial neural network controller controls the duty cycle of DC/DC converters in order to control panel and wind turbine output voltages.

In Fig. 43, change of solar irradiance for 1 day is given. Fig. 44 shows conventional control system output and Fig. 45 shows artificial neural network output. As shown in these figures, artificial neural network controller is better than the conventional controller for stabilizing the output voltage. ANN controller reduces ripples on output voltage.

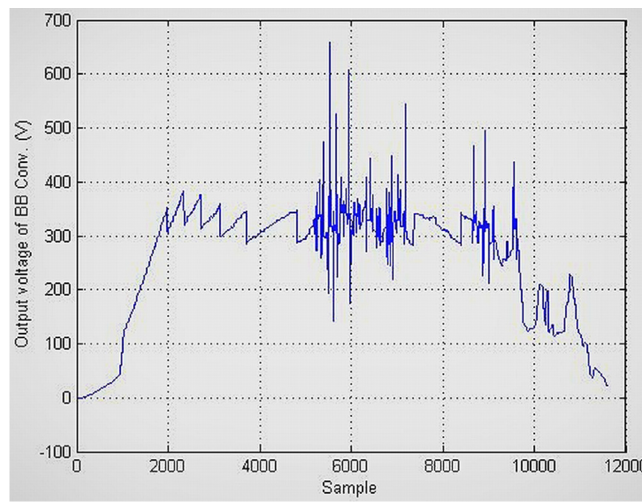

**Fig. 45.** Output voltage when ANN controller used [91].

## 5. Conclusion

Interpretation capability and decision ability of artificial neural networks have been used in many different areas for control systems. Nowadays, conventional control strategies for renewable energy area are changing with intelligent systems. Artificial neural networks are holding a big position within these intelligent systems with their ability of humanlike thinking.

Artificial neural networks (ANN) have an increasing usage area in PV technologies. Most usages of ANN technologies on PV are prediction of solar irradiance with related power generation, modeling of PV cells and modules, maximum power point tracking simulations and applications with ANN.

For wind turbine conversion systems (WECS), ANN structures have been used for wind energy prediction, pitch angle control designs, modeling of WECS, controlling the maximum power generated from WECS and improving system efficiency.

Artificial neural networks have been used for controlling PV and wind power in many simulation works. However, there are a few application projects in this area. Especially control of hybrid renewable power systems using neural networks do not have many application projects in the world. According to simulation results of most of the completed studies, neural networks have better performance than conventional control methods. Because neural networks are similar to human brain and they can make interpretations when unknown environmental situations occurred, they deserve better system performance and better power quality. In the near future, it is expected that neural network structures will find place in more renewable energy applications. With neural networks, renewable power stations will work more efficiently and their working cost will reduce.

## Acknowledgment

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